Exhibit 13

UNITED STATES DISTRICT COURT

DISTRICT OF NEW JERSEY

IN RE: Aetna UCR LITIGATION,

MDL: 2020

Master Case No. 07-3541 (FSH)(PS)

This Document Relates To: ALL CASES

EXPERT REPORT OF STEPHEN FOREMAN, Ph.D., J.D., M.P.A.

August 9, 2010

(CORRECTED)

Contents

I. Introduction

1. Individual plaintiffs are members or subscribers of defendant Aetna's health insurance plans who received reimbursement from Aetna for out of network medical care. Plaintiffs have brought a class action against defendant Aetna and defendant Ingenix, a health insurance service firm that provided percentile data to defendant Aetna that was used to reimburse plaintiffs. Ingenix is a subsidiary of UnitedHealth Group. Individual plaintiffs also include providers who received reimbursement from defendant Aetna for medical care rendered to members or subscribers.

2. Association plaintiffs include the American Medical Association, the American Podiatric Medical Association, the New Jersey Psychological Association and a number of state medical associations/ societies. The Association plaintiffs allege that they have expended considerable time and effort helping their members deal with defendants' reimbursement policies.

3. Individual plaintiffs believe that they have been under-reimbursed because the percentile data used by defendant Aetna to establish "reasonable and customary" limits on billed charges for out of network medical care were biased downward.

4. A related case, In re Aetna UCR Litigation, asserts similar claims against defendant Aetna-US Healthcare.

5. I have been retained as an expert witness on behalf of plaintiffs to render a report regarding flaws in the Ingenix percentile data, the impact of the flaws and damages relating thereto.

6. My opinions are based on (1) generally accepted principles and methodology used in industrial organization economics as applied in health care settings and in antitrust cases, (2) fundamental principles of health care economics and finance as taught in university health administration programs and (3) fundamental principles and methods used in advanced quantitative methods in health care that include econometrics and statistics.

7. I have more than 30 years of experience in health economics, health care law, health care finance and health care administration. I have been a hospital chief executive officer. I currently teach doctoral and master's courses in health economics, health care finance, health policy and health law and ethics at Robert Morris University in Pittsburgh, Pennsylvania.

8. In my work I study health care reimbursement as it relates to health insurers, subscribers, and providers. I have authored peer reviewed journal articles relating to various aspects of health economics and health policy.

9. I have served as special expert for the Attorney General of New York State during the investigation of health insurance firms' use of the Ingenix percentile data bases for payment of out of network claims on behalf of enrollees. During the course of the investigation, I reviewed health insurance claims records supplied by a number of health insurance firms, including defendant, compiled data distributions to establish billed charge percentiles and compared the percentiles of the data distributions with the PHCS percentiles that were used for payment for out of network physician services.

10. I have served as special expert to the contract monitor for the New York Attorney General's project involving production and distribution of unbiased, transparent billed charge percentiles for the purpose of health insurance firms' payment of out of network claims (the FAIR Health Project). In the course of the FAIR Health project, I was appointed Senior Research Professor at Syracuse University in which capacity I worked with colleagues from Syracuse, the University of Rochester, Cornell University, the University of Illinois, Chicago, the University of Colorado, the State University of New York, Albany, and others to develop a plan for an interim correction for the PHCS and MDR percentile tables and a plan for permanent changes to the databases by developing and implementing methodologies that will make them as accurate and transparent as current science allows.

11. I have testified before the US Department of Justice and Federal Trade Commission as well as federal and state legislative bodies regarding health insurance and physician reimbursement. During the course of this testimony I provided opinions relating to health insurance market definition, health insurance industry entry barriers and the structure and performance of health insurance markets.

12. I have investigated various aspects of health policy market and have authored reports summarizing this work for a number of national and state professional organizations. I am a frequent speaker on these issues.

II. Summary of opinions and findings

13. The concept of "usual, customary and reasonable" (UCR) or "reasonable and customary" (R&C) is an industry term of art and is used in health insurance reimbursement. The phrase includes a geographic component and a product or service component expressed as usual, customary and reasonable for the "same or similar services in the community."[1]

[1] *See, e.g.,* AET-00000502-509.

14. Percentile data compiled at the geozip level neither reflects a geographic market for medical care services nor a community.

15. Percentile data that uses procedure codes (CPT codes[2]) that combine billed charges from physicians and non-physicians and all types of physician specialists does not produce references for the "same or similar" services.

16. The percentile data provided by Ingenix that were used by defendant Aetna to reimburse patients and providers was not compiled in accordance with sound statistical or econometric principles.

- The data are used to produce percentiles for that serve as a surrogate for UCR in order to limit reimbursement. Ingenix applies an outlier screen to censor or eliminate data. There is no scientific justification for applying an outlier screen to percentile data. The outlier screen eliminates data whether they are outliers or not. The outlier screen produces a bias in the percentile data.
- Modifiers are used in the CPT system when medical care procedures do not follow a standard pattern. Ingenix keeps some data with modifiers but eliminates others. There is no scientific basis for the Ingenix policy relating to modifiers. The inclusion of modifiers in the data bias percentile values upward or downward depending on the modifier.
- The data are contributed by less than all health insurers. Almost 65% of the contributor medical surgical data used by Ingenix are contributed by Aetna, United, CIGNA and Wellpoint. The data collection process has not been developed scientifically and there is no scientific indication that the data are representative. There are indications from the data itself that the data are not representative. Failure to provide representative data more likely than not produces a bias in the percentile data. A reasonable estimate of the bias is six percent to 12%.
- The majority of the Ingenix percentiles do not reflect actual billed charges but are derived. There is no scientific rationale for derivation when there are sufficient data to report percentiles using actual billed charges. The derivation process is not scientifically based or verified. The derived percentiles bear little or no relationship to billed charges

[2] Current Procedural Terminology is a set of medical care procedure codes developed and copyrighted by the American Medical Association.

for the same or similar services in the community. The derivation process produces a bias in the percentile data.

- Percentiles are reported for CPT codes in geographic areas when there are nine or more billed charges. There is no scientific basis for this practice. Statistical principles suggest that in order to provide appropriate confidence that the percentile values are "accurate" (within 2.5 percentiles of the percentiles observed and reported) for a CPT / geozip with a population of300 billed charges requires a sample of 254 or more billed charges. Percentiles reported for nine to 254 billed charges are essentially random if there are more than ten actual billed charges for the CPT / geozip during the year.
- Percentiles are developed for CPT codes by including billed charges from all providers (nurse practitioners, ambulance drivers, chiropractors, podiatrists, family practitioners, anesthesiologists, neurosurgeons, radiologists and psychiatrists) regardless of qualifications and training. The services of these providers differ substantially, even though the same CPT code may be used during the billing process. Failure to deal with provider qualifications and training means that the percentiles do not reflect billed charges for the same or similar services in the community and, for a particular provider, are likely to be biased.
- Percentiles are developed by collecting billed charges in a geographic area called a "geozip" (an area described by the first three digits of a zip code). The geozip bears no relationship to a geographic market or a community. As a result the geozip percentiles are essentially random.

17. There is no scientific basis for use of comparisons of Ingenix percentile values to percentiles in individual health insurance firms or percentiles in physician billing software as a means for evaluating bias in the Ingenix percentiles. Scientific assessment of bias requires evaluation of percentiles compiled without problem processes.

- An empirical comparison using the Ingenix contributed data shows downward bias in percentiles when the outlier screen is used.
- Empirical comparison using the Ingenix contributed data shows that most modifiers influence or bias billed charges. Empirical comparisons show that the inclusion of modifiers provides downward bias in percentiles.
- Empirical analysis using the Ingenix contributed data shows that the contributed data are not representative of all health insurers' billed charges. Empirical analysis shows

that the lack of representativeness likely produces downward bias in percentiles. A reasonable estimation of the representativeness bias is 6% to 12%.

- Empirical analysis using health insurance firm and contributor data shows that billed charges (for the same CPT code) differ substantially and significantly among different providers and specialties.
- Empirical analysis using health insurance firm and contributor data shows large variation in billed charges within a geozip. Use of the geozip produces biased percentile data.
- Empirical analysis using health insurance firm and contributor data shows that use of insufficient numbers of data produce wide variation in percentiles year to year for the same CPT / geozip combinations. Use of inadequate data to report percentiles results in biased (essentially random) percentiles.
- Empirical analysis using health insurance firm and contributor data shows that the derivation of percentiles produces biased percentiles and that the bias is downward.

18. Contributor data have been made available for 2006-2008. Contributor data percentiles calculated without the flawed Ingenix processes provide more accurate values.

19. Two independent analyses of percentile values at the 50th, 60th, 70th, 75th, 80th, 85th, 90th and 95th percentiles using Ingenix contributor data from 2006-2008 (the very data used to construct the PHCS and MDR rate tables) show substantial and systematic downward bias in the Ingenix percentile tables.

20. Comparison of the percentile values in MDR with the same percentile values in PHCS finds PHCS values biased downward by three to four percent even though the same data are used for both.

21. A study by one of defendant's experts is consistent with, indeed proves, the existence of systematic downward bias attributable to the high-low screen.

22. The same contributor data compiled *without applying the high-low screen, without time delay effects, without small numbers reporting issues, without modifiers and without derived data* – produce higher percentile values on a consistent basis than the comparable Ingenix PHCS 80th percentile values. These findings compel rejection of the hypothesis that the Ingenix percentile values are not biased downward and acceptance of the null hypothesis that they were.

- Collectively, all medical surgical percentile values for the contributor 80th percentiles (computed without the Ingenix problems) were higher than the equivalent PHCS percentile values in two large contributor data studies (with 90,000 and 157,500 CPT/

geozip combinations. Overall, the contributor 80th percentiles were11.2% higher for medical surgical claims – regard to the representativeness issues discussed above.

- The same comparison indicates that collectively all of the dental percentile values for the contributor data were 9.8% higher than the PHCS dental values.

23. The results of the comparison of downward bias in Ingenix provide the basis for estimating damages either by adjusting the amounts allowed on a global basis or conducting a line by line analysis of what was allowed for each claim compared to what should have been allowed.

24. If the court determines that use of the Ingenix percentile data was not appropriate to limit reimbursement based on UCR and that defendant should have reimbursed billed charge, a reasonable damage estimate would be of $ 3,119,554,255 (for medical and surgical claims and for dental claims) as determined by summing the difference between billed charges and allowed amounts for all out of network reimbursement using Ingenix products or similar methods, less an adjustment for deductibles, copayments, coinsurance and coordination of benefits for all out of network claims. These amounts have been calculated for each year that reimbursement data are available from defendant Aetna and estimated for the years for which data are not available.

25. If the court determines that use of percentile data for UCR is appropriate but that the Ingenix percentiles were flawed, a reasonable estimate of damages of $ 2,081,450,906.

- This consists of two amounts, the first $1,387,633,937 based on the requirement that Aetna should have paid more accurate allowed amounts, excluding adjustments for interest, lack of representativeness of the data, for training and experience and for geographic variation. This value is determined by (1) using the Ingenix contributor data to generate more accurate percentiles, (2) measuring the difference between "accurate percentiles" and percentile values contained in the Ingenix products as a percentage, (3) adjusting amounts "allowed" by defendant to reflect the percentage difference between the Ingenix products actually used and the "but for" accurate percentiles and (4) calculating damages as "accurate allowed" less actual allowed, less an adjustment for deductibles, copayments, coinsurance and coordination of benefits for all out of network claims adjudicated using the Ingenix percentiles (or an equivalent) for R&C.
- A reasonable damage estimate based on percentile bias related to use of non-representative data is$ 693,816,969.

- It is possible to construct damage estimates that deal with the failure of the percentile tables to consider provider qualifications and training and to construct damage estimates that reflect use of inappropriate geographic areas.

26. A reasonable damage estimate for Association plaintiffs' time and effort in dealing with the out of network payment issues is $3,371,848.

III. Education, experience and qualifications

27. My educational background includes:

- A PhD in Health Policy and Administration from the University of California, Berkeley with a concentration in Health Economics (1994).
- A Master of Public Administration from the Kennedy School of Government, Harvard University (1989).
- A Doctor of Jurisprudence with Honors from the University of North Carolina (1976).

28. I currently serve as Associate Professor of Health Administration and Economics at Robert Morris University, Pittsburgh, Pennsylvania, where I teach courses in microeconomics, macroeconomics, health law and ethics, health care finance and health economics.

29. I have served on Governor Rendell's Task Force on Health Care Reform and currently serve on the patient safety committee of a health system in Southwest Pennsylvania. I serve as advisor for medical care payment and health insurance for the Delaware Valley Health Care Coalition, a health purchasing cooperative of more than 200 unions.

30. I have served as an expert to the New York Attorney General for out of network health insurance payment issues and as an expert to the contract monitor (and Senior Research Professor) for the New York Attorney General's FAIR Health project involving the establishment of accurate and transparent percentile for out of network health insurance payment.

31. I have testified on several occasions before the U.S. Department of Justice and the Federal Trade Commission relating to competition in health insurance markets on topics that have included market definition and barriers to entry.

32. I have worked with the AMA to develop an ongoing study of health insurance markets and the levels of concentration in those markets.

33. I have testified before the US Senate Judiciary Committee on concentration in health insurance markets.

34. On behalf of the Medical Society of New Jersey, I have evaluated a proposed physician fee schedule for automobile accident injuries developed by Ingenix consultants.

35. I have recently completed service as a Fulbright Scholar, providing lectures in health policy including health administration, health insurance, health care management, health economics, health care finance at Crimea State Medical University, Simferopol, Crimea. I prepared a White Paper on national health reform in Ukraine published by the Crimean Verkhovna Rada that included a proposal for a private health insurance program.

36. My previous experience includes work as a nationally recognized hospital revenue bond finance attorney and service as a health system president and chief executive officer.

37. I provide health economics and health administration consulting services for state government, medical societies, law firms and labor organizations. These services include reviews of the structure and performance of the health insurance industry and provider reimbursement.

38. I have prepared and continue to prepare and conduct peer reviewed research and publications in the areas of health policy, health administration and management, health economics, health care finance and health care law.

39. My curriculum vitae is enclosed as Exhibit A.

IV. Materials reviewed

40. In preparation for this report I have reviewed the materials contained in Exhibit B.

V. Factual background

41. Historically, medical care was "fee for service." Patients received medical care from physicians, physicians billed them for services rendered and patients paid "out of pocket." (Raffel, Raffel, & Barsukiewicz, 2002).

42. Health insurance for physician services originated at Baylor University in 1929. The first physician insurance plans were called "Blue Shield" plans. Blue Shield "reimbursed" physicians on behalf of patients for the physician's "billed charge." Blue Shield reimbursed physicians so long as their fees were not higher than the fees charged by other physicians in the area, the "usual, customary and reasonable (UCR) payment system. (Sandy, Bodenheimer, Pawlson, & Starfield, 2009). As other providers' services began to be insured, the UCR system was extended to them. As other health insurers began to provide coverage for medical care they too adopted the UCR system.

43. When Medicare was developed in the 1960s, the program reimbursed providers on a fee for service basis as well. The usual, customary and reasonable system was used by Medicare order to limit payment. (Oliver, 1993).

44. During the 1980s preferred provider organizations (PPOs) and point of service plans (POS) and other health care financing products began to offer coverage that reimbursed most or all of the cost of medical care claims for patients who received care from a network of physicians retained by health insurers ("in network" providers) and a different level (usually a specified percentage) of costs for care received from out of network providers.

45. Reimbursement for out of network medical care is often limited by contract to "usual, customary and reasonable" billed charges or to "reasonable and customary" billed charges. [3]

46. UCR is an industry term of art. It is understood that UCR provides a comparison of a physician's billed charges to the charges that that physician generally provides (usual and customary) with charges to other physicians ("reasonable") in the community or geographic market. The comparisons relate to "the same or similar services" in a geographic area ("the community"). (Raffel, Raffel, & Barsukiewicz, 2002).

47. At some point traditional fee for service insurers began fixing UCR using a percentile of billed charges. At first the percentiles were established "in house" using the firm's data. As many Blue Cross and Blue Shield firms held a monopoly over health insurance, their data encompassed most of the transactions within a community. Later, a number of commercial health insurance firms began fixing UCR by pooling their data through the Health Insurance Association of America (HIAA) to produce percentile values. The data were called the Prevailing Health Care Charges system or PHCS. In the late 1990s HIAA sold their PHCS database to UnitedHealth Group.[4]

48. Concurrently in the 1980s and 1990s a Salt Lake City firm, Medicode, began providing a physician fee product to smaller health insurers and physician offices. The fee levels in the Medicode product (called Medical Data Research or MDR) were generated using a combination of survey data and derivations. In the late 1990s United also bought Medicode. [5] United put MDR and PHCS into its Ingenix subsidiary.

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[3] See, e.g., AET-00000502 at 509-510 (Owens Corning Plan); AET-00296986 (Reasonable and Customary Policy Overview).

[4] Deposition of Carla Gee ("Gee Depo.") dated March 17, 2010 at 27:3-4.

[5] INGENIXMDL001120029 at 030.

49. Like CIGNA, for most out of network claims Aetna has used PHCS.[6] Two Aetna subsidiaries including Aetna Student Health (Chickering) used MDR percentile data to establish reimbursement limits.[7]

50. Some health insurers, including CIGNA and Aetna, use the term "reasonable and customary" rather than "usual, customary and reasonable."[8]

51. In practice, Aetna considers reasonable and customary or reasonable or usual and customary to be a percentile of billed charges for the same or similar service in a specified area.[9] (Aetna, 2010). CIGNA and Aetna determine the percentage of billed charges using percentile data furnished by Ingenix.[10]

52. While some health insurers makes it clear to members "If there are not enough charges (less than 9) in the databases for a service in a particular zip code, we may use "derived charge data instead" (Aetna),[11] CIGNA does not appear to make such disclosures.

53. The MDR and PHCS are maintained using data contributed by some but by no means all, of health insurers. The number of data contributors decreased from over 200 contributors in 2000 to

[6] Deposition of James Cross ("Cross Depo.") dated March 23, 2010 at 75:2-14; Deposition of Maureen Altier ("Altier Depo.") dated October 26, 2007 at 99:6-20.

[7] Cross Depo. at 70:16-71:16. A number of legal actions contend that Chickering used outdated MDR percentile rates. New York Attorney General Settlement (2009).

[8] AET-00000502 at 509; AET-00000600 at 656-657; AET-C 0000995 at 1038; AET-00296986; CIG000651356 at 358.

[9] Cross Depo. at 66:21-68:11; *see also* Deposition of Wendy Sherry ("Sherry Depo.") dated February 12, 2010 at 39:16-42:10. Aetna has recently begun to use other R&C determinations using Medicare and other sources. Cross Depo. at 182:7-183:17. Similarly in June 2008, CIGNA under its Maximum Reimbursable Charge terminology began providing both the option of determining out-of-network reimbursement using Ingenix percentile data or using a percentage of Medicare. Sherry Depo. at 41:11-43:8; CIG000623420 at 429. Reimbursement under those systems suffers from the same problems as use of the Ingenix data.

[10] Cross Depo. at 66:21-68:11; Deposition of Deborah Justo ("Justo Depo.") dated March 25, 2010 at 168:23-169:5; Sherry Depo. at 39:16-42:10; CIG000623420 at 422.

[11] Cross Depo. at 79:10-80:22. In actuality, except for the top 150 CPT codes in the MDR medical module, which have both actual charges and derived charges, all of MDR is derived and substantial portions of PHCS are derived. Gee Depo. at 148:2-150:17; Deposition of Susan Seare ("Seare Depo.") dated July 13, 2010 at 50:5-10; INGENIXMDL000950390.

slightly more than 100 contributors in 2009.[12] Not all contributors contribute all of their data.[13] Ingenix does not measure and most likely does not know what portion of physician billed charges are included in their database for a given procedure and geographic area.

54. The MDR and PHCS provide a number of "modules" that include medical and surgical billed charges, anesthesia charges and HCPCS charges (generally for supplies and equipment). [14]

55. The PHCS and MDR data are contributed by health insurance companies. The contributed data include the physician's billed charge, the medical care procedure (CPT code), the place of service (Geozip), date of service, in network and out of network service, allowed charges, payment modifiers, and (sometimes) physician specialty.[15]

56. The data are processed by Ingenix using a number of processing algorithms.[16]

57. In 2008 an investigation by the New York Attorney General found a range of problems with use of the Ingenix data to pay out of network physician claims. "We conclude that the consumer reimbursement system is code blue and needs dramatic reform to protect consumers... Analysis discloses that for ordinary doctor's office visits, the Ingenix databases understate market rate by up to 28 percent across the state."[17]

58. Analysis of the PHCS and MDR by Dr. Bernard Siskin has found that the collection and processing of the data posed a range of problems including the lack of representativeness of the contributed data, inappropriate use of a high/low screen to reduce percentile levels, use of dated data and the absence of any procedures to audit data submissions for completeness or accuracy in a setting in which some of the contributors prescreened their data and contributed less than all of their data. Siskin 2004 Report at pp. 2-12.

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[12] INGENIXMDL000696332; INGENIXMDL000754414; INGENIXMDL000248741 at 742 (133 data contributors in 2008); INGENIXMDL000185872 at 873 (Email stating 108 contributors as of May 2009).

[13] Justo Depo. at 88:11-22.

[14] Gee Depo. at 28:14-29:25; INGENIXMDL001120029 at 031.

[15] INGENIXMDL000778017

[16] INGENIXMDL000457826 at 828 (Affidavit of Susan Seare ("Seare Aff.") dated March 25, 2005, ¶14).

[17] New York State Attorney General, The Consumer Reimbursement System is Code Blue, Executive Summary ("NYAG Report").

59. Empirical analysis of the contributed Ingenix data confirms that the MDR and PHCS percentiles are flawed, that the flaws bias the percentile values contained in the Ingenix products and that the bias is downward.

A. The New York Attorney General Investigation

60. In 2008 I worked as an expert econometrician and statistician with the New York Attorney General evaluating billed charges for selected medical procedures in five New York counties and comparing percentiles developed from all billed charges from all health insurers in these five counties with the percentiles contained in the Ingenix PHCS.

61. Data from all health insurers who paid billed charges for selected procedures in the five counties were subpoenaed for the years 2002-2007. Descriptive statistics were generated using Statistical Applications Software (SAS), a well-known industry standard statistical applications software package used by health economists, econometricians and statisticians.

62. Medicare claims data were obtained from CMS in the form of limited data set five percent carrier files for 2006 and evaluated using SAS.

63. Ingenix PHCS rate tables were obtained for 2006 and 2007.

64. Percentile distributions were generated using SAS for the selected CPT codes for all health insurers as well as for several individual carriers (United, CIGNA and Aetna) using the subpoenaed New York data.

65. Percentile distributions were also generated from the Medicare data.

66. The distributions and percentiles for all New York, Medicare and United, CIGNA and Aetna were compared with the PHCS tables. A simulation was developed that compared amounts allowed by United, CIGNA and Aetna and all carriers at the 75th percentile to amounts that would be expected to have been paid if the 75th percentile were established using actual billed charge data. The results of the comparisons are described in the New York Attorney General Report: The Healthcare System is Code Blue.

67. Nothing in work that I have performed since the time of the Attorney General report leads me to believe that any of the previous work or the findings contained in the Attorney General Report are incorrect. For the purposes of this report, I am not relying on the New York data or any of the work product from the 2008 investigation.

68. The New York Investigation concluded with a number of settlements with United and other health insurance firms (deferred prosecution agreements) which provided that the PHCS and MDR

would be transferred to a new nonprofit firm (FAIR Health) that would change the way that the data are collected, processed and distributed in order to provide for greater accuracy and transparency, and that the health insurance firms would use the new data for payment for out of network physician claims.

B. FAIR Health

69. FAIR Health is a nonprofit corporation established to assume responsibility for production and distribution of the MDR and PHCS rate tables in an accurate, transparent and open manner as well as providing consumers with a way to ascertain and compare out of network physician pricing.

70. The New York Attorney General and FAIR Health have tasked an independent group of researchers from a number of prominent New York universities (and others) with developing and implementing recommendations for modifications to MDR and PHCS to achieve the objectives of accuracy and transparency for the data and the rate tables. The universities involved (the Upstate Research Group) have included Syracuse, Rochester, Cornell, SUNY Buffalo, Colorado, Robert Morris and the University of Illinois, Chicago, and SUNY Albany.

71. An independent contract monitor has been tasked with ensuring that both FAIR Health and the Upstate Research Group accomplish the tasks envisioned for the project.

72. I was retained both as independent expert to the contract monitor and as a senior research scientist at Syracuse to help provide assistance and leadership to the project.

73. The changes to MDR and PHCS will be accomplished in two stages or phases. In Phase One the Upstate Research Group will make recommendations to FAIR Health regarding temporary changes that can be accomplished given the expediency of time and available data to make the rate tables more accurate and transparent. For Phase Two the Upstate Research Group will make recommendations to FAIR Health regarding full and complete overhaul of the data and the rate tables in order to provide optimal accuracy and transparency.

74. I am not relying on any data gained or developed from the FAIR Health project or the New York Attorney General investigation in providing this report.

C. Health Reform

75. The recently enacted Health Reform Act adds a new provision relating to medical reimbursement data centers. These centers will "develop fee schedules and other database tools that

fairly and accurately reflect market rates for medical services and the geographic differences in those rates." Health Reform Act, §10101 (Mar. 2010).

76. Clearly, it was the intent of Congress that fair and accurate data can be used for reimbursement that reflects usual, customary and reasonable market rates for medical care and geographic differences in those rates.

77. Congress intends that new medical reimbursement data centers will use best available statistical methods data processing technology to develop fee schedules and database tools, that the fee schedules and data base tools be regularly updated, that health care cost information be available on the Internet and that information about statistical methods be published and data be made available.

D. Ingenix

78. Ingenix markets percentile rate tables to health insurers for use in limiting payment to medical care providers for out of network services.

79. There are very few other firms that supply percentile software.[18] (Committee on Commerce, Science and Transportation, Office of Oversight and Investigations, 2009). The products offered by other firms have a very small market share and are developed using surveys or Medicare RBRVS.[19]

80. Ingenix holds most of the market for percentile data products.[20] (Committee on Commerce, Science and Transportation, Office of Oversight and Investigations, 2009). This market power can be a problem.

81. One of defendant's experts, Dr. Noether, in her Responsive Class Certification Expert Report dated May 28, 2010, makes light of the Ingenix market power problem by quoting from a 1996 study by (me and my colleagues) of Blue Cross and Blue Shield health plan conduct in the 1980s:

> The fact that the Plans seem to be using economies of scale (greater size) and monopsony power to reduce their costs and that they seem to be passing the reductions along to their customers suggests that contestability theory (or the expectation of competition) may well be operating in the market for health insurance.

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[18] INGENIXMDL000456618 at 625 (noting only key competitor is Captiva at Ingenix all-hands meeting); INGENIXMDL000541071 (competitive analysis of Ingenix's only competitor – Captiva).

[19] AET-00913905 (white paper discussing Captiva); INGENIXMDL000541071 at 80 (competitive analysis of Captiva).

[20] INGENIXMDL000541071 at 79 (Ingenix stating is owns 80% of the benchmarking market).

82. Dr. Noether's reliance on that study is misplaced and ignores what has happened in the world of health insurance over the past 30 years, much less the past ten. It certainly ignores much of the work that I have done since the time of that article and testimony to the contrary that I have provided – before the US Senate, the US Attorney General and the FTC.

83. The 1996 study considered nonprofit Blue Cross firms, not large national for profit health insurers like CIGNA and Aetna. Blue Cross firms in the 1980s had incentives not to misuse market power and to pass plan savings along to their members. CIGNA and Aetna do not. Their incentives are to pass savings along to their shareholders and to incentivize management. Any review of one of their SEC Annual Reports or quarterly reports (10-K and 10-Q) will show this.

84. Health insurance markets have consolidated over the past 15 years leading to real market power problems. This has been reviewed and discussed at all levels of government. Despite high levels of profits there has, in fact, been little or no new entry into the industry suggesting that it is no longer contestible.

85. In order to build its rate tables Ingenix collects data from health insurers relating to billed charges from medical care providers. The data are contributed "voluntarily" in the sense that Ingenix reduces the amounts it charges for its products for data contributors.[21]

86. Ingenix has lost data contributors during the ten years.[22]

87. The data are contributed by health insurers and third party benefit administrators of self-insured plans in exchange for reduced prices for the percentile rate tables. Ingenix states that it requires data contributors to certify:

- Data are from actual claims
- Data is not altered
- Place of service zip code has been provided
- Only non-discounted fee-for-service charges are included
- Data represents 100% of claims received for the submission period.[23]

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[21] INGENIXMDL000257826 at 830 (MDR/PHCS Data Contribution Manual); INGENIXMDL000018489 at 492 (Affidavit of Susan Seare dated March 14, 2008, ¶ 30); Gee Depo., p. 35

[22] INGENIXMDL000696332; INGENIXMDL000754414; INGENIXMDL000248741 at 742 (133 data contributors in 2008); INGENIXMDL000185872 at 873 (Email stating 108 contributors as of May 2009).

[23] Gee Depo. at 44, 83-85, 368-369; INGENIXMDL000202216 (Data Contribution Submission Form); INGENIXMDL00004623 (2010 Data Contribution Submission Form).

1. Accuracy and representativeness of the data

88. The Ingenix data certification requirements are relatively new (post 2005).[24] Ingenix does not perform any statistical analysis to ascertain whether contributors comply with the data submission certifications.[25] As described in the Siskin Report, several depositions and documents, at least one large contributor, Aetna, did not comply with the certifications and applied internal editing to the data it contributed to Ingenix.[26]

89. Aetna's representatives state that Aetna applied a "profiling" process prior to submission of data to Ingenix.[27] Other characterizations state that Aetna "removed outliers" from the data before submitting it to Ingenix with the understanding that Ingenix would also remove outliers.[28]

90. At some point, Aetna representatives made it clear to Ingenix that Aetna had not complied with the certification.[29] Ingenix representatives initiated a dialogue that concluded with issues of an altered certification. Ingenix representatives contacted Aetna to convince Aetna to change its certification answers.[30]

91. It is not known whether Ingenix initiated any investigation of the impact of Aetna's policy on the percentiles it distributed or took any steps to correct any adverse impact on the data.[31] There is no indication in the record that it ever did so.

92. ARIMA time series analysis, econometric time series cross-section pooling, non-parametric distribution comparisons and other forensic techniques can be used to determine whether there has been a change in the composition of data contributed by a carrier over time or whether there

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[24] INGENIXMDL000754244; Justo Depo. at 100:1-102:15; INGENIX000754736

[25] Gee Depo. at 91-93

[26] Justo Depo. at 88:11-90:1.

[27] Justo Depo. at 88:11-90:11

[28] AET-01163366.

[29] INGENIXMDL000754244; Justo Depo. at 118:13-154:20; INGENIX000754736

[30] *Id.*

[31] Deposition (Rough) of Wendy Larsen ("Larsen Depo.") dated June 29, 2010 at 113; Justo Depo. at 118:13-154:20.

has been tampering with the data. The PHCS data contributions have not been subjected to such analysis.32

93. There is no way to determine what portion of the total of all billed charges in a geographic area claims are represented by the Ingenix data. Ingenix does not perform statistical analysis to ascertain the representativeness of the data contribution or to correct for any lack of representativeness. Siskin 2004 Report, pp. 27-28. Siskin Supp. Report, p. 12.

94. The data are contributed "voluntarily" (based on financial incentives) by health insurers.[33] The contributors have an inherent conflict of interest. NYAG Report.

95. After the New York attorney general investigation Ingenix conducted an investigation of its data. The results of that investigation have not been made public.[34]

96. To the extent that insurers contribute higher billed charge values to Ingenix, the Ingenix rate tables will increase and the amount that they pay providers will rise. Therefore, insurers have incentives not to contribute higher billed charges. Insurers that reimburse at higher levels have incentives not to contribute their data at all.

97. To the extent that health insurance firms who do not contribute data to Ingenix have higher physician billed charges the Ingenix percentiles will be biased downward.

2. The high-low screen

98. Ingenix engages in what it describes to be a "data validation" process.[35]

99. The validation process includes consideration of whether the data has a valid zip code, a valid CPT code, whether the dates of service are appropriate, whether modifiers could potentially impact fees and eliminating data that would be otherwise unreliable.[36]

100. The data validation process includes a procedure in which values below and above a given percentile are eliminated from the data.[37] This procedure is imposed to deal with outliers.[38]

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[32] Gee Depo. at 92-94

[33] INGENIXMDL000257826 at 830.

[34] Seare Depo. at 226:8-228:25

[35] INGENIXMDL000109228 at 236 (Ingenix Benchmarking Products presentation

[36] Seare Aff. ¶¶ 23-24; Gee Depoo. at. 54:2-23; INGENIXMDL000109228 at 236 (Ingenix Benchmarking Products presentation).

101. The high-low screen used by Ingenix is similar to a high-low screen developed in the 1980s by Tukey to identify outliers. (Tukey, 1977). Tukey's identification did not propose automatic elimination of extreme values identified as outliers.

102. The validation process eliminates data if it falls outside a range computed with reference to a multiple of the 50th percentile and 80th percentile calculated using prior years' limits.[39]

103. The Ingenix high-low screen commonly eliminates five percent of the data and for some contributors more than 10% may be eliminated.

104. Billed charge claims data are not expected be normally distributed. They would be expected to be right skewed because there cannot be a billed charge less than zero.[40]

105. Scientific theory does not justify formulaic rejection of medical claims data used to construct percentile nonparametric data distributions on the basis that they are outliers. Scientific theory does not support identification of more than one half of one percent of data elements as outliers in a data set that has enough information to permit computation of percentiles. (Gravetter & Wallnau, 2008).

106. The high-low screen is likely to provide a downward bias to the Ingenix rate tables. Siskin 2004 Report at p.12.

107. The Ingenix high-low screen does not identify "outliers" based on current data. The values that fix the high-low screen are developed using prior period data, not current data.[41]

108. The high-low screen limits in advance the values that percentile rate tables can take on in future time periods. The way that the limits are applied has the potential to create a "regression to the median" for the percentile data.

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[37] Seare Aff. ¶¶ 23-24; Gee Depoo. at. 54:2-23; INGENIXMDL000109228 at 236 (Ingenix Benchmarking Products presentation).

[38] Gee Depo. at 84:24-87:23

[39] *Id.*

[40] INGENIXMDL000189345 at 384-86 (Gee testifying in First Care Chiropractic Center, Inc. v. Progressive Ins. Co., Case no. SCO-03-9095, that she would expect billed charge distribution to have a long right tail).

[41] Gee Depo. at 84:24-87:23

109. The high-low screen fixes in advance (not based on the data) limits on percentile values that will be produced when data are collected and processed during later periods.

110. In a right skewed distribution that is reflective of medical care billed charges, the impact of the high-low screen will be to eliminate expensive billings from the data and to reduce allowed amounts because the dollar value of expensive procedures eliminated will be far greater than inexpensive procedures. The screen will have the effect of collapsing the range of the billed charge data which will, in turn, have the effect of identifying substantial numbers of observations in the data as outliers. Use of prior period data to calculate the high-low screen (rather than current data) has the effect of limiting upward increases in percentile limits even when the market evidences medical care cost inflation.

3. Modifiers

111. Many billed charges are submitted with "modifiers." Modifiers are an indication that something out of the ordinary has occurred in connection with the medical care procedure. Modifiers provide a wide range of information. They include indications that a charge is a professional component of a procedure that has a technical or equipment charge associated with it. They can indicate reduced efforts (modifier 52) or increased efforts (modifier 22). They can indicate the side of the body for a medical procedure (left or right). They can indicate that a procedure was done on both sides of the body (modifier 50). They can indicate that a procedure was distinct and different from another even though provided the same day (modifiers 25 and 59). They can include multiple procedures performed at the same time (modifier 51).

112. Ingenix keeps "many" billed charges with modifiers but drops others.[42] There is no indication that Ingenix has scientifically investigated the relationship between billed charges and modifiers. If physicians alter their billing based on the modifier it would not be appropriate to use the billed charge with the modifier as a point of reference for UCR and it would not be statistically appropriate to include billed charges with modifiers when developing percentile data since the modified billed charge would provide a source of bias.

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[42] Seare Depo. at 111:2-114:10

4. Small numbers issues

113. HIAA started the practice of reporting billed charge percentiles for geozip / CPT combinations for which there are nine or more billed charge claims.[43] However, this practice does not relate to any statistical method that produces any level of confidence that the percentile value reported is accurate. To the contrary, billed charge amounts and distributions for geozip / CPT combinations where there are nine or more charges can produce sizeable random variation, variation that makes the reported percentiles a guess.

114. In effect, Ingenix is concluding that a sample with nine or more billed charges provides percentiles that reflect, with scientific confidence, the percentile of billed charges in the population of all billed charges.

115. Such statistical confidence requires a proper power analysis to determine the number of claims needed in order to build percentile rates for which any appropriate level of confidence. The power analysis must incorporate a margin for error as well as specifying the width of the percentile range – a confidence interval.

116. Moreover, there are hundreds of thousands of CPT/ Geozip combinations for which there are not even ten claims records.[44]

117. There is evidence that Ingenix has recognized the small numbers issue and has researched it.[45] One internal analysis of the issue resulted in a recommendation that Ingenix not report percentiles with less than 50 claims.[46] Despite this, Ingenix has continued to report percentile values for CPT/ geozip combinations with as few as nine claims.

118. As noted above, Aetna's agreements and disclosures state that where a service is "unusual, not often provided or provided by only a small number of providers" payment will be made based on complexity, the degree of skill, provider specialty, the range of services or the

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[43] INGENIXMDL000950390; Gee Depo. at 148:22-149:8; Seare Depo. at 63:21:64:4 (testifying that Ingenix uses nine occurrences as threshold because that's the way HIAA developed it).

[44] Seare Depo. at 49:18-50:10 (testifying that 89-90% of the codes in the PHCS database are derived) and only10-11% .are based on actual charges).

[45] Seare Depo. at 64:8-65:13.

[46] INGENIXMDL000666852 at 854.

prevailing charge in other areas. However, Aetna does not do this. Instead, it uses MDR and PHCS data.[47]

5. Derived percentiles

119. All of the MDR percentile limits are produced using relative value imputation. A number of the PHCS percentile limits are produced using this technique.[48]

120. No scientific justification for data pooling is provided for geozip / CPT combinations for which there are sufficient amounts of data to establish percentile limits. The imputation process means that the billed charge percentiles contained in MDR are derivations. They do not represent percentiles for the same or similar medical care procedures in the community.

121. The process permits imputation of a derived value for geozip / CPT combinations for which are few or no data for the establishment of percentile limits.

122. The process divides billed charges for a procedure by a relative value for the procedure developed "internally" by Ingenix, then arrays these "normalized" amounts, finds percentile values for the array and multiplies back the relative values for the CPT codes to impute a percentile value.[49]

123. PHCS derivations are produced using a different relative value for the same CPT codes than for MDR. This produces different percentile limits for the same geozip and CPT combination for MDR and for PHCS.

124. Accuracy for the process is dependent on accurate relative values. MDR relative values are different from PHCS relative values and both of these are different from Medicare relative values. Procedures for verifying accuracy of the relative values are not disclosed and there is no indication that the relative scales used for MDR and PHCS have been independently or scientifically verified.

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[47] Cross Depo. at 79:10-80:22. Indeed, the MDR and PHCS relative value imputations for HCPCS (supplies and goods) assume that syringes, ambulance services and wheelchairs are the same or similar services.

[48] INGENIXMDL000950390; Seare Depo. at 50:5-10.

[49] *See generally* INGENIXMDL000109228.

125. In addition to CPT codes, PHCS and MDR combine data among geozips in order to reduce the number of geozip / CPT combinations for which there are insufficient data to provide percentile limits.[50] The same distortions occur when data are combined by geozip as for CPT.

126. The MDR and PHCS produce varying values for the same CPT/geozip percentile. The variance can be more than ten percent.[51] There is no indication that Ingenix has investigated the magnitude of the difference or its implications or that it has warned customers and the public about the discrepancy.

127. Some health insurers use both MDR and PHCS. This means that it is possible that different family members could receive different reimbursement for the same medical procedure provided by the same physician on the same day.

6. Differences in training and experience

128. For a given CPT code the Ingenix rate tables do not differentiate among providers based on licensure, specialization, experience or similar qualification.[52] .

7. The geozip

129. According to Ingenix, PHCS and MDR data are organized by three digit zip code (the geozip) and by medical procedure (the CPT code).[53]

130. The concept of usual, customary and reasonable relates to the same or similar procedures a locale – often described as "the community." In essence, UCR limits to billed charges because the market does not impose price discipline for medical care services. Markets are geographic in nature and follow consumers' purchasing preferences.[54]

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[50] INGENIXMDL000209228 at 249.

[51] Deposition of Carla Gee ("Gee Depo. II") dated March 18, 2010 at 19:9-25:22.

[52] Gee Depo. at 236:14-238:1;

[53] Seare Aff. ¶ 26; Gee Depo. at 220:6-20; INGENIXMDL000109228 at 237 (Ingenix Benchmarking Products presentation).

[54] Ball Memorial Hospital v. Mutual Hospital Insurance, Inc., 784 F.2d 1325 (7th Cir. 1986);

131. In effect, the percentile data uses the geozip as geographic point of reference. This amounts to a hypothesis that the geozip is the relevant community or geographic area for establishing prevailing charges and reasonableness.

132. In fact, the geozip is merely the first three digits of the zip code for the place of medical care service. The post office has established zip codes for mail delivery, not with any kind of reference to community or places where consumers would be willing to go for medical care service. Geozips bear no relationship whatsoever to medical care markets. Siskin 2004 Report, p. 10.

8. Billed charge inflation and the effect of time

133. The concept of UCR is a "current time" concept. Billed charges from providers are compared with billed charges from other providers *at the same time*. When percentile values are used to measure UCR the process of collection of data, compilation of percentile values, packaging of the product, distribution of the product and implementation of the product by health insurers consumes a substantial amount of time. Failure to recognize and "control" for the effect of time has the potential to provide another source of downward bias to the Ingenix products and to their use in the UCR process. By the very nature of the process, Ingenix and the health insurers hypothesize that billed charge inflation does not impact percentile values that are used in the UCR process.

134. Ingenix updates its MDR product four times each year and applies an inflation factor to it using the consumer Price Index. Ingenix updates the PHCS product two times each year but does it not apply an inflation factor to it.[55] The product does not specify inflation parameters.

135. In order to maintain currency the Ingenix products use a "one year moving window" for the data underlying the product.[56]

136. Despite efforts within Ingenix to keep the product current, the very nature of it imposes a substantial time lag on the percentile values that are used for UCR.

137. The process of development of the PHCS product, for example, encompasses the following steps as a summary:

- collection of the data from health insurers

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[55] INGENIXMDL000950390.

[56] Gee Depo. 144:13-145:5.

- scrubbing and processing of the data
- compilation of percentile values
- incorporation of the percentile values in a software product
- distribution of the product to health insurers
- incorporation of new software in health insurer claims processing
- use of the data for claims processing

138. In practice the PHCS and MDR process flow sheets each require four pages to describe. And those flow sheets do not deal with health insurer collection and submission of data.[57]

139. Working backward, suppose a health insurer updates its percentile product twice per year. At the end of the product use cycle the percentile data is six months old. If it took one month to incorporate the new processing software in the health insurers system the data are seven months old. If it took Ingenix three months to prepare the product and one month to distribute it, the data at the end of the product cycle are 11 months old. The data used in the product encompass the previous year. If all health insurers are current in their data contribution at the end of cycle that percentile data are now 23 months old. If health insurers contribute substantial amounts of data at one time during the year the percentile data at the end of the product cycle can be 29 months old.

140. The time required for data collection, data processing and data implementation provide a substantial lag that is not accounted for in the products or their use. The process presumes that there is not substantial inflation in billed charges. If there is such inflation then percentile values will be biased downward when they are used for UCR.

141. There are data and statistical techniques available to identify billed charge inflation that can be used to "correct" for downward bias that has resulted from collection and processing and implementation time. (Brockwell & Davis, 2002). Neither Ingenix nor the health insurers have used these techniques in implementing UCR.

9. Collective application of problems

142. Each of these data problems occur collectively and in combination producing permutations. The high-low screen, for example. disproportionately eliminates expensive services. Failure to consider provider training and experience or expensive geographic areas may mean that reimbursement of billed charges from some providers and from some locations

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[57] INGENIXMDL000013812-13819.

will inevitably be reduced. In addition to the specific problems produced by each part of the methodology, from a mathematical standpoint the number of permutations suggests that result of aggregating these problems may well not be linear: The total of the problems taken together, likely exceeds the sum of the individual issues.

143. The number of combinations and permutations of the problems makes the damage estimate in this report conservative. It would be nearly impossible to reverse engineer the Ingenix processes to ascertain the effect of any single practice. The most effective and reasonable approach – which we have undertaken – is to compare percentiles from data like the contributor data (or all billed charges obtained by subpoena) with the results of the Ingenix processes contained in the percentile data products.

144. Much of the foregoing begs the question, "What would have happened 'but for' the production and distribution of the flawed percentile rates and their application by health insurers?"

VI. Issues relating to Ingenix percentile values

145. There are seven known issues relating to the Ingenix percentile values:

- Representativeness
- Elimination of data using the high-low screen
- Use of modifiers
- Reporting percentiles using small numbers
- Data derivation
- Failure to recognize provider qualifications and training
- Use of the geozip as a surrogate for geographic markets

146. I have undertaken empirical analysis of each of these issues using Ingenix contributor data from 2006-2008[58] and Aetna claims data for 2001 to 2008.[59] In addition, I have

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[58] INGENIXMDL000756673.

59 ACAS Claim Data, including AET-00500964 (2004), AET-00500965 (2003), AET-00297211 (2005), AET-00500967 (2001),

undertaken an empirical analysis of percentiles generated from the contributor data without the processing issues compared to the Ingenix post processing percentile values contained in its products. There is empirical confirmation of flaws in the Ingenix process and that Ingenix percentile values are biased downward.

VI. Ingenix billed charge percentile product issues

A. Representativeness

147. Health insurers use the percentiles provided by Ingenix to establish reimbursement limits for UCR. Health insurers limit reimbursement above a specified percentile (for example the 80th) to the specified percentile billed charges. The process presumes – hypothesizes - that the Ingenix percentiles represent a specified level of billed charges defining "reasonable" for the same or similar services in a community: That the Ingenix percentiles are unbiased.

148. The billed charge data that Ingenix uses to create the percentiles do not include all of the billed charges (the entire population) for a service in an area. If they did, the Ingenix percentiles would in fact be an accurate representation of a population parameter – percentiles of billed charges. However, Ingenix does not collect data from all health insurers and some insurers contribute less than all of their data.[60] It does not appear that Ingenix knows how much of the billed charge data they collect for any area and there is no indication that it has undertaken any attempt to do so.

149. A "population" is a group that represents all of the members of the group, here the population of all billed charges during a particular time in a particular area. (Urdan, 2005) A "sample" is a subset of the population. The goal of inferential statistics is to use data from samples to reach appropriate conclusions about populations. (Gravetter & Wallnau, 2005). In order to generalize from a sample to the population, the sample must have certain scientific characteristics. That is, it must be representative. A sample is biased if, on average, it fails to provide an accurate estimate of a population parameter. (Gravetter & Wallnau, 2005). In

[60] *See, e,g,*, INGENIXMDL000542148 (indicating that in 2003 Aetna contributed data relating to 5.5 million enrollees, CIGNA, 5.4 million and United, 3.4 million at a time when each firm had well over ten million enrollees).

order for the Ingenix percentiles to be unbiased the Ingenix sample must permit an inference that it is representative of the entire population of billed charges.

150. In order to draw inferences about a population parameter on the basis of a sample – to prove the hypothesis – the sample must be selected randomly and the parameter estimate from the sample must be compared to a distribution of theoretically similar estimates from samples of the same size that might be selected from the population and the probability that the sample parameter reflects the population parameter must establish the validity of the inferences. (Hinkle, Wiersma, & Jurs, 2003).

151. The Ingenix data are a "convenience sample." They may even be a "snowball" sample. A convenience sample (also called a "grab sample") selects data on the basis of proximity, ease of access and willingness to participate. In order to be scientifically appropriate the convenience sample cannot differ from the population of interest in ways that influence the outcome of the study. (Urdan, 2005).

152. Ingenix does not know what portion of the population of data that its data represent. It has apparently undertaken no efforts to investigate the representativeness of its data.[61]

153. The Ingenix data do not represent all of the billed charges in a geographic area for a period of time. Indeed, empirical analysis of the Ingenix medical surgical contributor data from 2007 indicates that less than 100 firms contributed data. See Table 1.[62] Indeed, many of the contributors are third party administrators and self-insured plans. In addition, as noted above, some of the contributors do not contribute all of their data. Table 1 does indicate that the data contributors may not, in fact, be representative of health insurers generally.

Table 1
2007 Ingenix Data Contributors
Source: Ingenix Contributor Data INGENIXMDL000756673

Co	**Name**	Company	**Name**
1	UNET_ United Heath Care	349	Unkn
2	GEHA_BG	356	Wells Fargo
6	Fiserv Health	357	UMR
25	Assurant	365	
29	Corporate Benefit Services	370	Great West Life /
31	Welfare and Pension Admin	371	BCBS of Minnesota - Medical
36	Group and Pension Admin	372	HealthNow New York Inc.
43	First Health-	374	American Medical Sec
55	Healthaxis (Insurdata)	375	Aetna
62	Health Alliance	382	
73	Unkn	385	HealthPlan Services Medical /

[61] Siskin 2004 Report, pp. 27-28; Siskin Supp. Report, p. 12.

[62] *See also* INGENIXMDL000929773.

77	Benefit Planners/	390	Highmark
84	Unkn	392	Regence BS of WA - Medical
87	Med Pay	394	CIGNA OHIO Medical
88	NGS (Trustmark)-med den	395	Stirling & Stirling
92	NALC-	396	Excellus BCBS of Rochester-
94	First Health /	399	Unkn
101	Unkn	401	HealthComp
102	SIHO	408	Boilermakers National Fund-
120	American Postal Workers Union	409	American Republic Ins-Medical
152	Unkn	411	Cigna of Tennessee /
171	ASU Group- Recovery Unlimited	415	HealthLink-
173	Unkn	417	Empire BCBS - Medical
177	Marshfield Clinic (Security Health Plan)	419	
179	Employee Benefit Management Corp	420	Sunlife (Fmr: Genworth - Den
184	CNIC Health Solutions	437	Horizon BCBS of NJ
206	Unkn	496	Unkn
208	Northwest Administrators	505	Unkn
212	Key Benefits	512	Harrington Benefit Svcs(many)
224	Employee Benefit Managment Services	522	Gilsbar
229	Wisconsin Carpenters ALL	526	First Administrators
239	Aetna Student Health	530	Medical Associates Health Plan
254	ATPA - Surgery	533	Secure One
296	BCBS of Massachusetts	549	Unkn
309	Medical Mutual Ohio	551	Coventry
324	Unkn	553	Unkn
334	ATPA - Medical	556	Alaska Electrical Health and Welfare
338	Unkn	559	Unkn
342	BCBS of North Dakota - Medical	566	Unkn
343	Wausau Benefits /	567	Unkn
345	Unkn	568	Meritain Health- National
346	Principal Financial	569	Premera BCBS
348	Cooperative Benefit Admin	570	Meritain Minneapolis

154. The National Ambulatory Medical Care Survey (NAMCS) conducted by the CDC indicates that there are about one billion physician office visits annually in the US. (Centers for Disease Control, 2010). Adding another 50% for visits to chiropractors, dentists, podiatrists and nurse practitioners and another 50% for laboratory tests yields approximately two billion medical care transactions annually in the US. If each transaction generates two claim lines there will be four billion claims lines annually – and none of this considers hospital based professionals.

155. In 2007 the Ingenix contributor data consisted of 1.4 billion claims lines – about half of them medical and surgical claims, one fourth dental and one fourth HCPCS. This indicates that Ingenix may be capturing substantially less than half of all physician billed charge data nationally and perhaps less than a third.

156. Given that the Ingenix data are a convenience sample contributed by health insurers, that no efforts are undertaken to measure or assure representativeness, what can be said about the relationship of the data to the population of all billed charges?

- The dominant data contributors are large health insurers, including defendant Aetna.
- Large national insurers generally pay physicians lower amounts than other health insurers because they have bargaining power.
- Physicians who bill at lower levels are more likely to participate in networks with large national insurers and are more likely to be represented in the Ingenix data.
- Insurers who pay physicians at higher levels have incentives not to report data.
- In short, there are reasons to believe that the convenience sample is not representative of all billed charges. In order to evaluate the hypothesis that the contributed data is representative of all billed charges we considered the mean billed charges for all transactions for all medical surgical data contributors to Ingenix for 2007. The results are set forth in Table 2.

Table 2
Mean Billed Charges for All Contributor Medical Surgical Procedures in 2007 by Contributor
Source: Ingenix Contributor Data INGENIXMDL000756673

Contrib	_FREQ_	CHARGE	Firm	Contributor	_FREQ_	CHARGE	Firm
349	315,545	41.71		417	15,235,530	150.07	Wellpoint
392	3,230,643	102.52		569	1,141,430	151.50	
365	8	104.38		530	106,436	153.05	
29	122,895	106.63		73	321,723	154.41	
526	787,664	108.52		401	1,421,862	154.63	
570	2,880,039	110.49		31	813,606	155.57	
206	1,859,215	112.76		208	594,752	156.05	
173	498,790	112.90		370	7,059,175	158.98	
559	59,964	113.62		533	30,995	160.36	
411	28,806,058	115.56	CIGNA	372	4,480,714	160.89	HealthNow
342	1,919,944	115.91		385	1,347,090	165.55	
179	330,336	116.00		390	4,835,475	165.80	Highmark
25	2,668,569	116.92		567	140,491	166.36	
94	10,026,686	119.07	1st Sac	356	2,614,137	166.66	
212	603,205	120.82		87	163,298	166.98	
338	522,549	122.31		408	430,804	167.59	
394	14,134,577	122.51	CIGNA-T	556	81,454	168.40	
171	56,573	122.52		102	231,806	169.49	
345	759,719	123.25		62	1,490,709	170.32	
374	863,108	123.43		395	132,446	174.73	
224	1,723,292	125.76		184	288,898	175.34	
36	1,610,584	126.21		101	119,266	179.21	

496	954,269	126.65		6	434,111	181.15	
568	1,800,116	126.79		229	194,812	183.78	
396	3,259,708	127.27		551	2,561,809	188.75	
522	460,865	127.71		120	755,961	189.31	
88	932,279	128.70		43	13,208,473	189.93	1st SLC
334	230,994	131.70		415	4,482,016	190.10	
309	5,731,643	134.45		566	713,767	190.54	
55	3,342,773	134.93		239	853,535	199.37	Aetna-Chick
348	438,148	136.68		77	3,034,984	207.94	
152	256,126	137.22		343	7,389,368	214.45	
434	4,740,515	137.35		512	5,408,842	217.01	
419	474,563	137.73		371	575,803	228.28	
382	2,908,451	138.53		2	1,536,693	229.28	
354	121,690	138.97		437	20,906,074	247.81	Horizon
375	113,158,157	139.75	Aetna	1	168,082,319	252.92	United
409	1,013,138	140.18		399	1,223,072	291.79	
296	21,308,134	140.37		92	733,367	320.78	
346	5,753,950	141.44		505	540,601	377.26	
553	746,358	142.21		84	646,038	381.74	
357	1,680,095	144.94		254	18,584	667.85	
549	297,782	145.19		324	1,355,361	672.52	
177	800,692	149.26		All	521,928,096	185.97	Total

157. Table 2 indicates that not only are the Ingenix data contributors not representative of all health insurers, it indicates that the percentile values in the contributor data are driven by three or four firms. The contributions of firms, United, Aetna, CIGNA and WellPoint, constitute more than half of the data contributed. Moreover, overall billed charge levels for defendants Aetna and CIGNA are substantially below mean billed charges in the data, indicating that these large data contributors have the potential to and, in fact are, providing a source of downward bias to the contributor data.[63]

158. In order to show the potential impact of the unknown missing contributors' data we removed the Aetna and CIGNA data from the contributed data. The mean billed charge for all of the medical surgical contributor data rose from $185.97 to $208.28, a 12% increase. If the

[63] The analysis also shows that nonscientific nature of the contention by defendants' experts that because Ingenix percentile values are higher than percentile values for a given firm such as CIGNA or Aetna, that this "proves" that the Ingenix percentiles are not biased. Such a comparison proves nothing more than the Ingenix contributor data percentiles are at one level and each contributor's percentiles many differ. Indeed, that United appears to pay better than average calls into question the report by one of defendants' experts that concluded Ingenix percentiles are higher than United's.

billed charges that are missing from Ingenix are similar to those for contributors other than Aetna and CIGNA[64] it is likely that the Ingenix percentiles are biased downward.

159. It may be that geographic area may account for the difference in payment levels. The hypothesis here is that the differences between Aetna and CIGNA and the other contributors are due to differences in their geographic markets, not fundamental price levels. In order to rule this out we narrowed the empirical analysis to geozips in New York State. Table 3 shows the results of this evaluation.

Table 3

Mean Billed Charges for New York Medical Surgical Procedures in 2007 by Contributor

Source: Ingenix Contributor Data INGENIXMDL000756673

Cont	_FREQ_	CHARGE	Firm	Cont	_FREQ_	CHARGE	Firm
556	1,814	54.48		569	2,950	161.67	
171	1,376	64.01		372	4,330,738	163.70	HealthNow
496	49,049	72.43		401	11,154	165.40	
94	1,492,719	80.13	FirstSac	567	8,294	166.95	
36	94,449	81.80		152	4,665	168.13	
62	2,482	85.78		92	8,781	172.57	
31	2,116	88.51		309	35,679	172.64	
348	6,426	89.10		370	216,205	174.12	
224	28,257	90.61		43	1,034,662	180.11	FirstHlth
102	602	97.23		356	68,620	181.28	
101	3,877	110.16		409	5,879	182.22	
25	115,674	110.17		551	83,911	182.94	
179	5,898	110.54		120	74,427	184.84	
173	7,923	112.37		395	13,067	187.28	
392	2,023	116.12		206	1,214	190.47	
374	46,072	118.37		357	8,476	196.06	
55	476,118	119.97		390	2,234,516	202.47	Highmark
184	1,161	120.88		2	55,922	204.48	
526	3,807	122.00		343	238,025	207.39	
382	367,875	122.24		1	24,937,840	208.33	UNET
568	131,647	122.81		385	7,113	213.95	
411	2,337,783	124.62	CIGNA_O	419	2,722	219.16	
530	27	124.85		522	2,930	227.69	
396	3,009,631	126.40		239	200,563	231.32	AetnaC

[64] Which is likely since Aetna and CIGNA's size permit them to reduce price which discourages higher billing physicians from participating in their networks.

212	12,128	127.03		415	6,528	232.59	
29	3,817	128.41		6	9,410	273.90	
394	1,302,319	129.98	CIGNA_T	349	163	275.68	
549	4,395	131.90		77	90,018	301.42	
559	495	132.35		512	51,920	310.70	
177	429	133.81		437	1,750,262	326.78	Horizon
296	14,422	135.74		533	116	341.07	
208	580	137.28		334	64	362.38	
338	8,165	137.44		73	328	386.91	
434	182,870	139.00		553	1,468	398.09	
375	14,879,614	146.46	Aetna	229	93	444.45	
88	9,297	155.37		399	1,322	448.96	
570	103,656	155.76		84	4,555	451.84	
354	6,876	156.29		505	6,810	471.07	
408	58,536	157.10		254	2	550.00	
346	199,012	158.74		324	116,724	763.14	
566	15,709	160.17		307	455	1,015.72	
417	11,092,601	161.03	Wellpoint		71,712,318	176.25	Total

160. The overall mean billed charge for medical and surgical procedures in New York for 2007 was $176.25. Again, Aetna and CIGNA billed charges are substantially below the mean: $146.46 for Aetna and $124-$130 for CIGNA. Again, the data are dominated by a few contributors. If we remove CIGNA and Aetna claims from the data the mean rises to $187.82, an increase of 6.6%. The influence of Aetna and CIGNA on the data does not appear to be a function of geographic differences in payment.

161. Dr. Noether, in her Responsive Class Certification Expert Report uses language from the Foreman initial class certification to suggest that bias due to representativeness is not a problem:

> [I]t is possible to develop accurate billed charge percentiles using CIGNA's billed charge data provided during discovery. CIGNA's enrollees generate millions of medical care procedures including provider visits on an annual basis. There is no reason to believe that provider charges for CIGNA patients differ systematically from the charges the same providers apply to medical care rendered to patients of other health insurers.... [T]here is no reason to believe that CIGNA's providers are not representative of providers in general.

162. The quotation is taken from the context of using CIGNA billed charges to develop percentiles to evaluate damages, a context that is totally different from the representativeness

issue. Moreover, knowledge and facts available at the time did not indicate that there was a representativeness issue with the CIGNA data. Contributor data analysis suggests, indeed proves, that there is a representativeness issue with the CIGNA data. This suggests not only that Dr. Siskin was correct in his observations about data collection bias but that damage estimates need to be made using a broader range of data such as data produced by subpoena from as many health insurers as can be justified or, at a minimum, the contributor data.

163. In short, the Ingenix data represent substantially less than all billed charges, nationally and by local geographic area. Data are contributed by some, not all, health insurers and not all insurers contribute all of their data. Because the entire population of billed charges is not known there is no way to scientifically prove or disprove whether the Ingenix billed charges are representative of all billed charges. The hypothesis that the Ingenix percentiles represent UCR can neither be proven nor disproven. However, empirical analysis of the contributor data establish that the contributor data do not appear to be representative at all. If the contributor data are any guide and the missing data contributors are similar to the firms other than Aetna and CIGNA, Ingenix percentiles are likely to be understated by 6.6% to 12%.

B. The "high-low screen"

164. Ingenix applies a "high-low" screen to automatically exclude data.[65] For each geozip/ CPT combination the 80^{th} and the 50^{th} percentiles are determined. The 80^{th} percentile is multiplied by a factor (approximately '2') and the 50^{th} percentile is multiplied by a different factor (one-third, for example). The high and low values become screens for data subsequently received. The multipliers differ for the type of data (surgical, medical, evaluation and management, anesthesia and HCPCS).[66]

165. The high-low screen eliminates data and pre-determines the range of data that will be accepted into the Ingenix system without any regard to likely error, the statistical distribution involved or the relationship of the eliminated values to the distribution. There is no scientific basis or rationale for elimination of the data.

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[65] Gee Depo, at 86-88.

[66] Gee Deoo, at 86:17-87:9.

166. Outliers impact averages and coefficients in parametric models. They do not inordinately impact percentiles. "Within" data ranges of five percent to 95% outliers have no impact on percentile limits. Improper elimination of outliers can change percentile limits. In normally distributed data only three observations in 1000 can be expected to fall outside three standards deviations of the mean. (Gravetter & Wallnau, 2008). Ingenix eliminates five to ten percent of data submissions.

167. Elimination of outliers is a concept that relates to data means and to econometric modeling coefficients. Outliers are described as "extreme values more than two standard deviations from the mean." (Urdan, 2005). When the mean or a model coefficient may be affected by values that are unusually large or small for the distribution, they may be eliminated to get a better picture of the mean or a better model coefficient. However, the median and other percentiles are not affected by such values and it is inappropriate to eliminate outliers from percentile data. (Urdan, 2005)

168. Ingenix does not appear to have undertaken any inquiry into the impact of the high-low screen on the data percentiles. It does have a policy that it will independently evaluate contributor data when more than 10% of the data are eliminated or if elimination triggers certain ratios.[67] Ten percent is a large amount of data to eliminate from a submission.

169. With one exception, none of defendants' experts has undertaken an empirical study of the impact of the high-low screen on percentile values. In the case of the single exception,[68] the evaluation was performed by applying the high-low screen to current period data rather than to subsequent data. Also, the effects were not measured in an iterative manner. The impact of the high-low screen over time serves as a drag on inflation of percentile values, reducing increases in billed charges over time.

170. I have conducted empirical studies of the impact of the high-low screen on defendants' data.

- A high-low Tukey screen analysis
- A study comparing billed charge and allowed amount inflation over time using both CIGNA and Aetna data
- A descriptive study of the impact of elimination of data

[67] Gee Depo. at 231-233.

[68] Responsive report of M. Noether on behalf of CIGNA.

1. High-low screen analysis using Aetna data

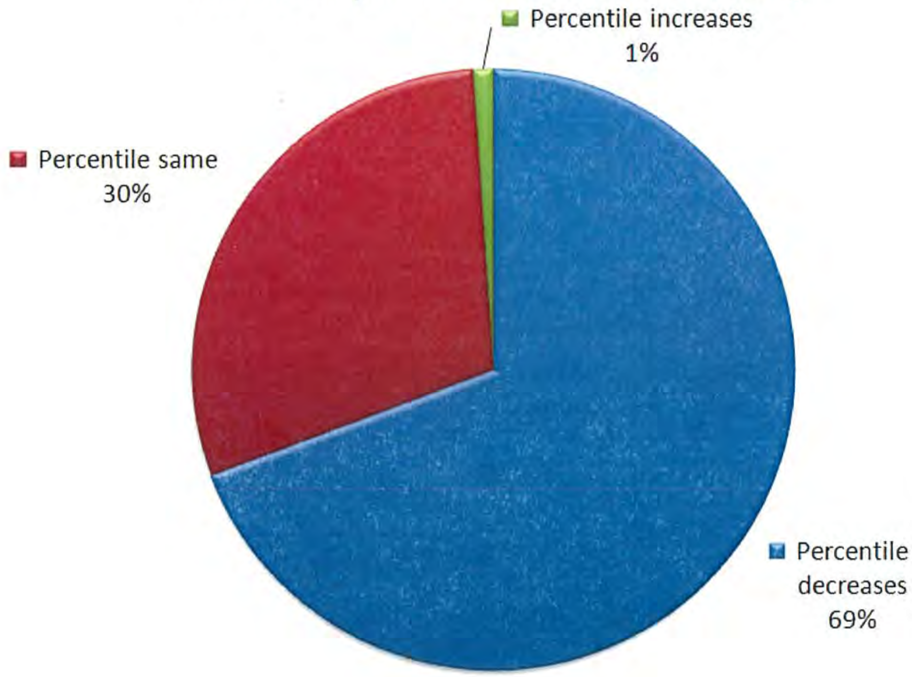
171. In order to assess the likely impact of a high-low screen on percentile values we extracted CPT codes 99211 through 99215 (office visit, existing patients) and 99201 through 99205 (new office visits) from Aetna's ACAS medical data to determine the effect that removing outliers using the Tukey method would have on the UCR. Because zip codes and geozps have been removed from the ACAS, and in order to keep the analysis simple we conducted the analysis at the state level. The ACAS data were medical data from 2008. The hypothesis was that removal of the Tukey outliers would not impact the percentiles in the data.

172. The distributions for these CPT codes/ geographic combinations are skewed right – there is a long tail on the distributions to the right.

173. We calculated the 80th percentile for each code by state as it was presented from the ACAS database and then calculated the 80th percentile again after removing outliers using the Tukey method. We performed the analysis using classic Tukey: (1.5 times the interquartile range minus the 25th percentile and 1.5 times the interquartile range plus the 75th percentile).

174. As shown in Figure 1, of the 550 CPT/state combinations, 381 (69.27%) resulted in a reduction of 80th percentile, for 163 (29.64%) there was no change and only in six cases was there an increase (1.09%).

Figure 1
Impact of High Low Tukey Screen on 80th Percentiles
E&M Codes (99201-99205 and 99211-99215)



175. Using Aetna ACAS medical claims data, the hypothesis that a high-low screen will not impact percentile values is rejected. The alternative hypothesis, that the high-low screen reduces percentile values in right tailed distributions is accepted. By using a Tukey screen to remove data the 80th percentile value was reduced or remained the same in almost every case.

2. High-low screen analysis using CIGNA data

176. We also used CIGNA PPO data and a classic Tukey screen to evaluate the impact of removal of data using a high-low" screen. Since there is deposition testimony that indicates Ingenix applies the multiplier to the 50th and 80th percentiles rather than the 25th and 75th, we used those percentiles for the screen.[69] Also, since the high-low screen is developed each year

[69] Gee Depo. at 86-88. We therefore apply the high-low screen to the 50th and 80th percentiles. The results are consistent and stronger when we use the 25th and 75th percentiles as in Tukey.

to eliminate data for the succeeding year, we applied the screen serially over time. Once again the hypothesis was that the high-low screen would have no impact.

177. The data used were CIGNA PPO data from 1999 to 2008. We considered the number of claims or observations in all of the CPT code / geozip code combinations and identified the ten geozips with the most data and the nine CPT codes with the most data. Table 4 lists the geozips and CPT codes selected for the study.

Table 4

CPT Codes and Geozips and Most Common CPTs and Geozips in CIGNA PPO Data

Geozip	Description	CPT Code	Description
070	Newark, Orange, NJ	90806	Psychotherapy, 45-50 min
100	Manhattan, NY	97110	Phys Ther, 15 min, strength range motion
117	Long Island, NY	97112	Phys ther, 15 min, reeducation of movement
600	Chicago, IL and north	97140	Manual therapy, 15 minutes
601	Western Chicago suburbs	97530	Therapy, direct patient contact
606	Chicago, IL and south	98941	Chiropractic manipulation
627	Springfield, IL	99212	Office visit, exist patient , problem focused
850	Phoenix, AZ	99213	Office visit, exist patient, expanded problem
852	Mesa, Chandler, AZ	99214	Office visit, existing patient, detailed problem
926	Irvine, CA	99215	Office visit, existing patient, complex problem

178. Accordingly, for the 90 most common CPT /GEO combinations we tracked the 80^{th} percentile from 2000 to 2008 - with and without the high-low screen. We started with the 1999 CIGNA PPO billed charge data. We developed values for the 25^{th}, 50^{th}, 75^{th} and 80^{th} percentiles of billed charges, the inter quartile range (IQR=75^{th}-25^{th}), the screen factor (1.5*IQR), the high screen value (80^{th}+(1.5*IQR)) and the low screen value (50^{th}-(1.5*IQR)). We then applied the screen to the 2000 PPO billed charge data, eliminating observations that exceed the high screen value and eliminating observations less than the low screen value. We computed the 80^{th} percentile for the 90 CPT/GEO combinations before and after applying the screen. We then take the post-screen data for 2000, develop the 25^{th}, 50^{th}, 75^{th} and 80^{th}

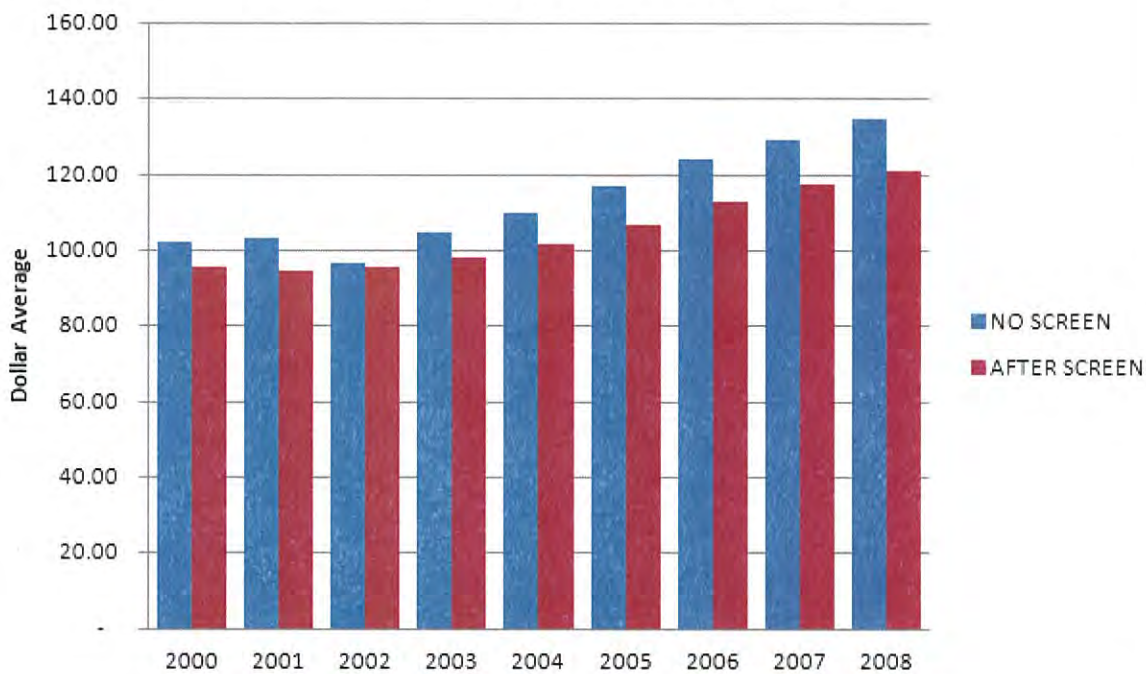
percentiles to build new screens for 2001 and repeat the procedure for 2001. The same steps were used for 2002-2008.[70]

179. Figure 2 shows the comparative values graphically year by year for the average of the 80th percentile values for all 90 CPT/ GEO combinations. The high-low screen consistently reduced 80th percentile values by a substantial amount.

180. Data Appendix 1 sets forth the underlying values used to develop Figure 2. Consistent with the Aetna study, using CIGNA data the high-low screen increased the 80th percentile value in twelve instances (seven of them in 2002). The high-low screen decreased the 80th percentile value in 523 cases. The high-low screen resulted in no change in 254 cases. The high-low screen consistently reduced 80th percentile values. As a result, we reject the hypothesis that the high-low screen has no impact on percentile values and accept the alternative hypothesis that the high-low screen reduces 80th percentile values in data distributions that are skewed right.

[70] Only six months of data were provided for 2008 but there were enough observations to produce a meaningful comparison for that year as well.

Figure 2
Average of 80th Percentile of Billed Charges With and Without High Low Screen



3. Billed charge and allowed charge over time – Aetna and CIGNA

181. In addition, we used Aetna and CIGNA data to investigate trends in billed charges and allowed charges over time. Defendants fix out of network payment – their "allowed amount - based on a percentile (often the 80th) of billed charges. Our hypothesis was that if the process that develops the "allowed" values is "neutral" over time, then billed charge inflation and allowed amounts should generally track one another. On the other hand, if the high-low screen or some other process acts a brake on billed charge inflation, we would expect to see billed charge inflation at higher rates than increases for allowed.

182. In order to test the hypothesis we extracted data for the 50 most common CPT codes in the Aetna ACAS data and for the 50 most common CPT codes in the CIGNA PPO data. We evaluated the average billed and allowed amounts for each of these codes by year.

183. Overall, as shown in Table 5, billed charges for the 50 procedures increased by $25.91 between 2001 and 2008 while average allowed amounts increased by $13.09.

Table 5

Change in Billed Charges and Allowed Amounts

50 Most Common CPT Codes Average Billed and Average Allowed

Aetna ACAS Medical Claim Data

	2001		2008		Overall	
IP_ID	CHG	ALLOW2	CHG	ALLOW2	BILLCHG	ALLCHG
36415	12.62	3.06	16.99	2.25	4.37	(0.81)
71020	100.93	44.02	191.81	67.10	90.88	23.09
80048	51.28	18.44	105.48	29.19	54.20	10.74
80053	54.82	20.57	99.02	32.68	44.20	12.11
80061	64.12	17.77	84.42	26.08	20.30	8.31
81000	17.29	4.76	19.09	4.48	1.81	(0.28)
81001	25.82	7.38	41.47	10.37	15.65	2.98
81002	12.80	1.20	16.07	1.45	3.28	0.24
82270	17.50	3.96	18.40	4.59	0.90	0.63
84443	75.58	22.66	95.97	32.45	20.40	9.79
85025	34.31	12.61	55.06	17.72	20.75	5.11
85610	26.26	9.65	42.95	11.20	16.69	1.55
87880	27.86	12.49	36.80	15.61	8.94	3.12
88142	59.99	23.80	71.75	32.05	11.76	8.25
88164	39.35	12.82	48.52	18.44	9.18	5.62
88305	183.28	71.41	306.81	114.92	123.52	43.51
90471	15.90	6.54	28.24	12.68	12.33	6.14
90472	22.94	8.34	34.95	17.11	12.01	8.77
90669	85.83	45.77	117.27	78.27	31.45	32.50
90806	117.04	48.23	133.04	67.60	16.00	19.38
93000	66.00	25.17	72.04	26.24	6.05	1.07
93010	36.82	6.87	39.19	7.86	2.37	0.99
95117	30.55	16.06	33.34	18.55	2.79	2.49
97010	25.67	6.78	26.72	4.67	1.05	(2.11)
97012	29.79	11.97	33.73	11.92	3.95	(0.06)
97014	29.56	11.70	33.07	11.38	3.52	(0.32)
97035	34.96	13.49	38.49	11.89	3.53	(1.60)
97110	86.25	37.97	110.22	46.02	23.98	8.05
97112	53.74	20.53	70.00	28.45	16.27	7.93
97140	60.45	24.76	76.09	30.64	15.64	5.89
97530	72.38	29.25	94.60	39.08	22.21	9.83
98940	42.83	18.31	47.37	21.32	4.54	3.00
98941	52.94	23.38	55.32	26.96	2.38	3.58
99000	17.03	7.45	18.68	0.01	1.65	(7.43)
99202	84.50	48.64	110.71	65.61	26.21	16.97

99203	115.84	66.81	160.58	94.66	44.74	27.85
99204	164.48	88.31	228.39	132.17	63.91	43.87
99211	41.99	16.74	58.26	21.29	16.28	4.56
99212	51.95	28.15	71.95	36.51	19.99	8.36
99213	66.73	39.23	93.00	56.85	26.27	17.62
99214	100.16	52.35	141.47	83.21	41.31	30.86
99215	151.71	74.23	207.81	111.74	56.09	37.51
99231	80.29	26.54	88.65	29.96	8.36	3.43
99232	112.54	41.11	128.10	49.10	15.56	7.99
99233	169.80	60.19	186.03	70.98	16.23	10.79
99243	172.91	87.84	227.06	128.03	54.15	40.18
99244	228.71	112.69	309.78	175.00	81.07	62.31
99283	220.69	87.73	358.23	174.60	137.54	86.88
Overall	71.65	30.89	97.56	43.98	25.91	13.09

184. Year by year, the percent increase in average billed and average allowed was as shown in Table 6. In five of the years billed charge percent increases were substantially greater than increases in allowed amounts. In two years increases in allowed amounts were substantially greater.

Table 6

Percent Change in Billed and Allowed by Year

Aetna ACAS Medical Claims Data – 50 Most Common CPT Codes

2001-02	2.3%	3.6%
2002-03	4.0%	1.8%
2003-04	3.2%	0.3%
2004-05	5.1%	2.7%
2005-06	2.8%	0.3%
2006-07	4.8%	2.2%
2007-08	4.1%	9.5%

185. The changes in average billed charges and allowed amounts are not similar year to year, or in the aggregate.

186. The differences in billed charge and allowed amount inflation suggests that the hypothesis that the process used to generate allowed amounts (the Ingenix percentile data) including the high-low screen, does not act as a brake on billed charge inflation, must be rejected. The Aetna ACAS data support the conclusion that some process or processes are acting as a brake on billed charge inflation.

187. We also tested the 50 most common CPT codes in the CIGNA PPO data for consistency between billed charge and allowed amount inflation between 2001 and 2008. Table 7 contains the results.

188. Overall, average billed charges for the 50 most common CPT codes for CIGNA increased $107.23 while average allowed amounts increases by $45.24. For CIGNA the billed to allowed ratio declined from 0.73 in 2001 to 0.60 in 2008. In 2001 CIGNA's allowed amounts were 73% of billed charges. In 2008 the ratio was 60%.

189. The outcome of this analysis is also inconsistent with the notion that the processes that generate allowed amounts were value neutral in terms of billed charge inflation.

Table 7
Change in Billed Charges and Allowed Amounts
50 Most Common CPT Codes Average Billed and Average Allowed
CIGNA PPO Data

CPT	2001 Billed	2001 Allowed	2008 BILLED	2008 ALLOWED	Overall Difference Billed	Overall Difference Allowed	Diff Pct Billed	Diff Pct Allowed	2001 Bill/Allow	2008 Bill/Allow
300	81.79	53.17	204.72	129.14	122.93	75.98	150.3%	142.9%	0.65	0.63
301	118.21	74.32	294.40	202.01	176.19	127.69	149.0%	171.8%	0.63	0.69
420	99.74	72.99	239.61	108.83	139.88	35.84	140.2%	49.1%	0.73	0.45
450	199.21	144.37	669.44	391.12	470.23	246.75	236.1%	170.9%	0.72	0.58
490	1,431.87	898.11	4,558.73	2,645.99	3,126.86	1,747.88	218.4%	194.6%	0.63	0.58
636	243.17	176.71	885.43	413.30	642.26	236.59	264.1%	133.9%	0.73	0.47
36415	16.77	12.98	23.56	12.02	6.79	(0.96)	40.5%	-7.4%	0.77	0.51
71010	41.81	29.34	41.63	19.70	(0.18)	(9.64)	-0.4%	-32.9%	0.70	0.47
71020	69.74	51.74	71.23	39.41	1.48	(12.33)	2.1%	-23.8%	0.74	0.55
80053	67.70	42.75	95.27	43.18	27.56	0.43	40.7%	1.0%	0.63	0.45
80061	72.03	50.64	260.78	193.82	188.75	143.18	262.0%	282.7%	0.70	0.74
81002	16.38	9.63	21.21	10.79	4.84	1.16	29.5%	12.0%	0.59	0.51
85025	34.03	27.02	49.89	26.40	15.85	(0.62)	46.6%	-2.3%	0.79	0.53
88305	236.17	172.27	342.42	181.42	106.25	9.15	45.0%	5.3%	0.73	0.53
90471	18.51	12.67	34.22	20.46	15.72	7.79	84.9%	61.5%	0.68	0.60
90799	411.42	259.99	48.05	31.95	(363.36)	(228.04)	-88.3%	-87.7%	0.63	0.66
90806	193.19	156.14	181.05	131.47	(12.14)	(24.67)	-6.3%	-15.8%	0.81	0.73
90807	253.73	206.57	124.87	89.24	(128.86)	(117.33)	-50.8%	-56.8%	0.81	0.71
90862	105.22	83.55	134.30	96.84	29.08	13.29	27.6%	15.9%	0.79	0.72
92012	73.47	52.13	97.90	40.67	24.42	(11.46)	33.2%	-22.0%	0.71	0.42
92014	88.18	62.95	127.70	55.21	39.52	(7.75)	44.8%	-12.3%	0.71	0.43
92507	152.65	114.91	140.59	80.50	(12.06)	(34.41)	-7.9%	-29.9%	0.75	0.57
93000	78.82	57.86	100.13	50.53	21.30	(7.33)	27.0%	-12.7%	0.73	0.50
93010	43.71	29.92	50.25	19.21	6.54	(10.71)	15.0%	-35.8%	0.68	0.38
97001	121.64	93.91	149.69	88.82	28.05	(5.10)	23.1%	-5.4%	0.77	0.59
97010	35.84	26.99	39.04	24.81	3.20	(2.18)	8.9%	-8.1%	0.75	0.64
97012	38.35	29.43	45.50	32.45	7.15	3.02	18.6%	10.2%	0.77	0.71
97014	39.50	29.83	45.12	31.36	5.61	1.53	14.2%	5.1%	0.76	0.70
97032	50.31	37.59	56.62	37.26	6.31	(0.33)	12.5%	-0.9%	0.75	0.66
97035	43.27	32.26	52.91	34.39	9.64	2.12	22.3%	6.6%	0.75	0.65
97110	99.63	69.01	105.76	72.98	6.12	3.98	6.1%	5.8%	0.69	0.69
97112	62.73	45.53	83.86	56.46	21.13	10.93	33.7%	24.0%	0.73	0.67
97140	77.57	59.06	93.43	67.47	15.86	8.41	20.5%	14.2%	0.76	0.72

97530	81.56	60.08	96.19	64.73	14.63	4.64	17.9%	7.7%	0.74	0.67
98940	51.05	41.70	59.15	45.47	8.10	3.76	15.9%	9.0%	0.82	0.77
98941	62.16	50.73	69.46	53.63	7.30	2.90	11.7%	5.7%	0.82	0.77
98942	75.97	61.38	84.40	61.12	8.43	(0.26)	11.1%	-0.4%	0.81	0.72
98943	48.86	38.38	57.19	42.40	8.33	4.02	17.0%	10.5%	0.79	0.74
99203	130.32	104.29	187.65	129.00	57.34	24.72	44.0%	23.7%	0.80	0.69
99204	192.98	152.13	283.07	178.91	90.09	26.77	46.7%	17.6%	0.79	0.63
99211	47.08	31.72	62.20	35.98	15.12	4.26	32.1%	13.4%	0.67	0.58
99212	55.96	44.05	89.96	55.71	34.00	11.66	60.7%	26.5%	0.79	0.62
99213	72.86	57.98	113.94	70.74	41.07	12.77	56.4%	22.0%	0.80	0.62
99214	117.48	90.15	168.47	101.83	51.00	11.68	43.4%	13.0%	0.77	0.60
99215	191.67	146.74	294.01	178.21	102.34	31.47	53.4%	21.4%	0.77	0.61
99231	119.19	82.45	126.59	61.94	7.40	(20.51)	6.2%	-24.9%	0.69	0.49
99232	150.76	108.51	164.35	78.30	13.59	(30.21)	9.0%	-27.8%	0.72	0.48
99233	257.59	181.41	252.73	122.78	(4.87)	(58.63)	-1.9%	-32.3%	0.70	0.49
99244	259.53	202.29	361.01	216.22	101.48	13.93	39.1%	6.9%	0.78	0.60
A0425	133.79	80.41	187.19	96.57	53.40	16.16	39.9%	20.1%	0.60	0.52
Overall	135.30	96.21	242.54	141.45	107.23	45.24	47.3%	21.3%	0.73	0.60

4. Descriptive analysis of the high-low screen

190. We used the CIGNA 2007 PPO data to generate descriptive statistics for the 10 common CIGNA geozips in order to investigate the impact of the high-low using PPO data. Table 8 shows frequencies, means, medians, standard deviations, skewness coefficients, the 80th percentile value and the high-low screen "cut" points, three standard deviations from the mean and extreme values for CPT Code 99213 – mid level evaluation and management (office visit and the most common CPT code). Table 8 sets forth the parameters.

Table 8
Descriptive Statistics for CPT 99213 by Geozip
CIGNA PPO Data

	70	100	117	600	601	606	627	850	852	926
freq	15,990	23,207	10,039	25,512	26,631	23,788	21,285	6,654	8,351	4,640
mean	86.69	143.57	92.65	87.7	87.4	94.43	71.87	84.65	82.64	99.97
median	80	140	80	85	85	90	61.51	80	80	84
std dev	28.09	95.53	36.68	25.3	24.62	33.67	17.55	25.65	26.08	420.87
skew	2.65	43.82	2.02	1.4	3.38	2.77	2.57	3.93	12.32	31.84
No Screen 80th	100	188	124	105	102	114	89	97.5	100	100
Screen 80th	100	175	95	105	100	111	88	90	90	95
Screen High	140	245	124	152.5	144	160.95	120.81	103	111.5	127.5
Screen Low	14	0	28	7.5	12	13.75	15.33	50	27.5	27.5
3 stds hi	170.96	430.16	202.69	163.6	161.26	195.44	124.52	161.6	160.88	1362.58
3stdlow	2.42	0	0	11.8	13.54	0	19.22	7.7	4.4	0
extreme1	325	1300	300	388	234	400	188	235.62	314	1080
extreme2	329	1395	325	388	295	400	188	235.62	314	14000
extreme3	401	2500	350	388	461.9	400	188	259	314	14000
extreme4	495	6500	360	395	461.9	400	191	400	477.9	14000
extreme5	495	8600	360	500	1075	600	642	630	1254	14000

191. Each of these geozips has a substantial numbers of underlying observations for 99213 (from 4,640 to 26,631). The mean values for these office visit billed charges are relatively similar. The medians are generally close to the means –suggesting that outliers are not an issue with the data. The coefficients of skewness are all positive and other than geozip 600, greater than two. This indicates that the data are strongly skewed right as might be expected with physician billed charge data. With the exception of geozips 926 and 100, standard deviations are not large. In eight of the ten cases the high-low screen reduced the 80th percentile value and in two cases there the screen neither increased nor decreased the 80th percentile.

192. The lines "Screen high" and "Screen low" show the screen values above and below which data are eliminated. The impact of the screen is illustrated three ways.

- First, we compare the high-low screen cuts to the traditional outlier estimation for normally distributed data, three standard deviations from the mean in both directions. Other than in geozip 926, the high-low screen values are lower at the high end and greater at the low end suggesting that the high-low screen eliminates more values than a three standard deviation measure would provide.
- Second, the five extreme values for the geozip are shown. Values are quite high for geozip 100 and for geozip 926, but they do not look like they are typographical errors and they appear to have some rationality. In the case of geozip 926 the four highest values are all the same, suggesting that they represent a very expensive procedure that was performed four times. All told, there are very few values that are so extreme that they appear to be outliers from observation: possibly (but not necessarily) all five extreme charges for geozip 100, the $1075 charge for geozip 601, the $642 charge for geozip 627, the $1254 charge for geozip 852 and all five extreme values for geozip 926. By contrast application of the high level at $103 (for geozip 850) and $245 (for Manhattan) removes a substantial amount of billed charge data that are clearly not outliers and that provide real information about equivalent billed charges. Also, the removal distorts the data.
- Third, we compare the high and low cut points to the 80th percentile values with and without the screen. Because the application of the screen provides downward reduction in percentile values the high cut points approach the 80th percentile values and in one case – geozip 117 – the high level cut point matches the 80th percentile value.

193. All of this illustrates, using CIGNA PPO data, how the automatic use of prior period high screen values to eliminate current period physician billed charge data from the data distributions works to bias percentiles downward by removing data in an inappropriate manner.

6. Professor Slottje's analysis

194. In a report dated July 30, 2010, on class certification issues professor Daniel Slottje reaches the following conclusions:

- Statistical testing ... contradicts plaintiffs' assertion that the "end result of this cycle of collusion [involving Ingenix and its contributors] is a database that produces flawed uniform pricing schedules... for [OON] services..."
- Specifically, the empirical evidence ... contradicts plaintiffs' hypothesis that the Ingenix Database "[r]eports charges that are systematically skewed downward.
- Empirical evidence also contradicts plaintiffs' hypothesis that Ingenix – through the use of its PHCS database – engaged in the "incorrect removal of valid high charges [biasing] the upper percentile values downward."
- Furthermore, the empirical evidence ... contradicts plaintiffs' hypothesis that Ingenix "further 'scrubs' the pooled data [it receives from contributors] to remove high-end values but not low-end outliers so as to lower the average price of [OON] benefits."
- Indeed, in performing the assignment given to me, I have found no empirical evidence to support plaintiffs' claims.

195. The sole empirical test that Professor Slottje engaged in was to take Ingenix data from 2006 through 2008 that had been "scrubbed" using the high-low screen and reversing the "scrub" to a deserved what happened to percentile values.

196. The very use of the term "scrub" is spin and has no statistical meaning. Ingenix has coined this term in order to imply that it makes the data somehow better. In fact, the high-low screen arbitrarily distorts data by censoring or arbitrarily eliminating values it does not like when it develops percentile values used for adjudicating UCR. There is no scientific justification for the elimination and Professor Slottje offers none.

197. Outliers may be removed from data when generating means because outliers distorts means and they may be removed from models for the same reason. Outliers do not impact percentile data so there is no justification for their removal in producing percentiles. Moreover, outliers have little impact at all on large data sets. The Ingenix contributor data are immense. Outliers should not impact

percentile values generated from the data. Professor Slottje offers no analysis at all of why there would be a need to remove outliers from the Ingenix percentile data.

198. Professor Slottje "found" that Ingenix "scrubbed" 6% to 7% of "eligible" records for being too high or too low. In essence, Ingenix concludes and Professor Slottje agrees that 6% to 7% of the contributor data are outliers, a conclusion so remote as to border on science fiction.

- In the case of normally distributed data one in 370 observations (0.3%) will deviate by three times the standard deviation (a common definition of outlers) from the mean. This is often termed the "three sigma rule."
- For Ingenix to conclude and for Professor Slottje to agree that its data contain twenty times more outliers than the norm has no meaning.
- There are a number of statistical tests for outliers. Ingenix uses none of them to justify its high-low screen, nor does Professor Slottje.

199. Professor Slottje found that (italics and bold type his)"

- "for roughly 85% to 88% of all CPT – geozip combinations based on actual charge data (740,000 combinations), Ingenix's application of the "Hi/Lo scrub" had ***zero*** impact on the percentile amounts..."
- Adding back in the high and low charges that Ingenix excluded due to the "Hi/Lo scrub," ***lowered*** the percentile amounts for 3% to 6% of all CPTgeozip combinations

200. Thus, Professor Slottje touts: *"adding back in the high and low charges that Ingenix excluded due to the "Hi/Lo scrub" either lowered, or had no impact on the percentile amounts for 89%-94% of all CPT-geozip combinations."* (Italics from Professor Slottje).

201. Professor Slottje's analysis fails to comprehend the impact of the "small numbers" issue on his findings. In addition to the derived values in the percentile data (3.2 million of them) a substantial number of CPT/geozip combinations report percentiles with very few claims (530,000 of 740,000-or more than 70%). The combinations with few claims might well be expected not to change based on the high-low screen. He should not be surprised that 85% of the percentile values did not change.

202. More important, Professor Slottje reports the "half empty" view of the world, ignoring the "half-full" side. If 3% of percentile values decreased after replacing the eliminated data and 85% remained the same, 12% of them increased. What Professor Slottje does not report is that replacing the eliminated data changed percentile values 15% of the time with increases compared to decreases in the

ratio of 4 to 1. This consistent with, indeed provides proof, of systematic downward bias in the PHCS data attributable the high-low screen.

203. Professor Slottje also fails to report which percentile values he measured. If he included the 50th percentile and 60th percentile values his study results would be expected (indeed foreordained) since the high-low screen primarily impacts higher level percentiles (80th, 85th, 90th and 95th). It is likely that the 12% replacement data percentile value increases occurred at the high end and that the 3%replacement data percentile value decreases occurred at the low end.

204. Most important, Professor Slottje fails to put a dollar value to his findings. As noted by Dr. Siskin, censoring of data at the high and low ends provides a much greater dollar reduction at the high end than a commensurate the dollar addition at the low end. Eliminating data relating to expensive procedures is not offset by eliminating a like amount of data for low cost procedures. If the ratio of billed charge amounts eliminated at the high end is ten times greater than the billed charge amounts eliminated at the low end, the 12% - 3% findings could easily translate into a ratio 40:1 for the dollar value of the percentiles reduced by the high-low screen to the dollar value increased.

205. In short, Professor Slottje's study of the high-low screen, despite his conclusions to the contrary stemming from failure to consider major portions of his findings, is fully supportive of the hypothesis that the high-low screen produces downward bias in the Ingenix percentiles. More important, it ignores other crucial issues that go to a consideration of bias in the Ingenix products.

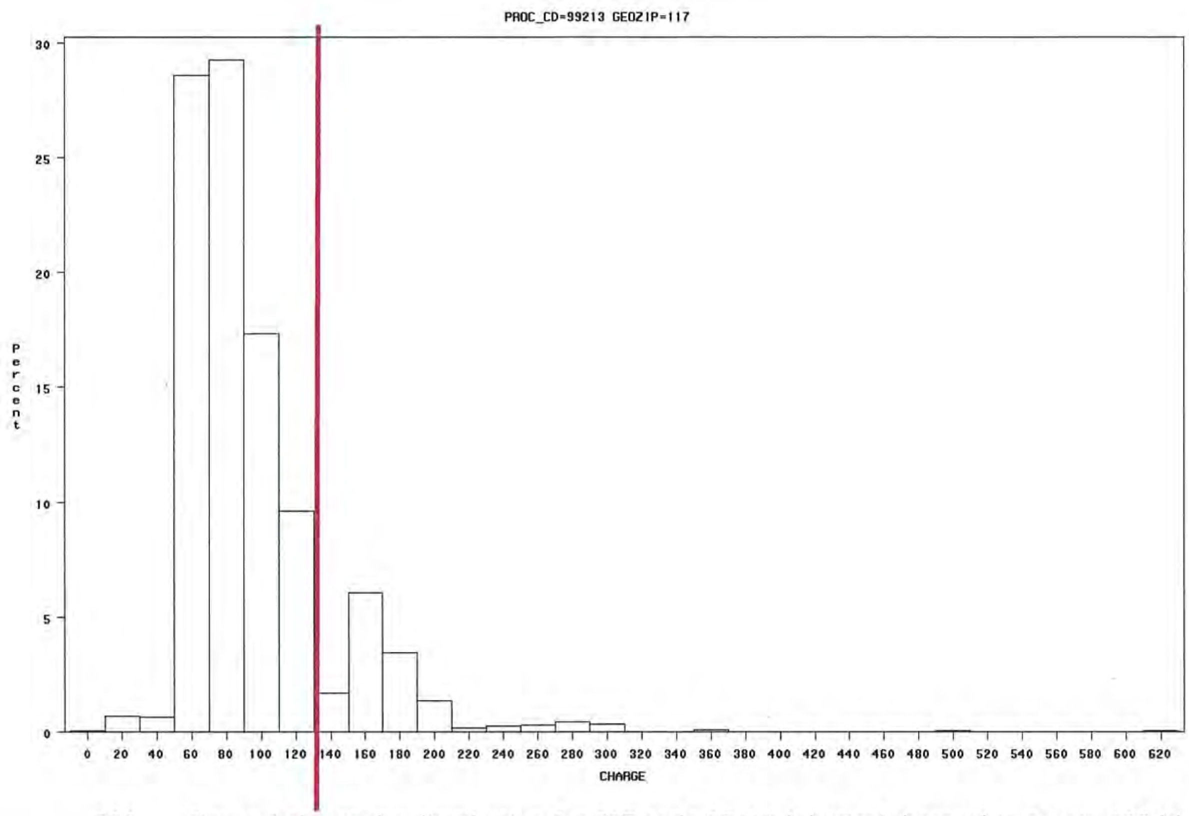
6. Visual analysis of the high-low screen impact

206. This can also be shown visually as well. For three CPT/ geozip combinations in the CIGNA data we developed histograms for the data distributions, then overlaid high-low screen cut points and the 80th percentile values with and without the screen.

207. Figure 3 below shows the distribution of CIGNA's PPO billed charges for CPT code 99213 in geozip 117 (Long Island) for 2007. The distribution is clearly skewed right with very few billed charges less than $60, substantial numbers of billed charges between $220 and $300 and clusters at $360, $500 and $620. The high-low screen eliminates all of the billed charges less than $28 (very few of them) and all of the billed charges greater than $124 (substantial numbers). Three standard deviations from the mean would identify billed charges greater than $202 as outliers. Visual inspection of Figure 3 and the extreme values at the high end of the distribution (three billed charges of $500 and two at $625) suggests that to define these billed charges as outliers would, indeed, be a mistake. Moreover, even if these five charges are

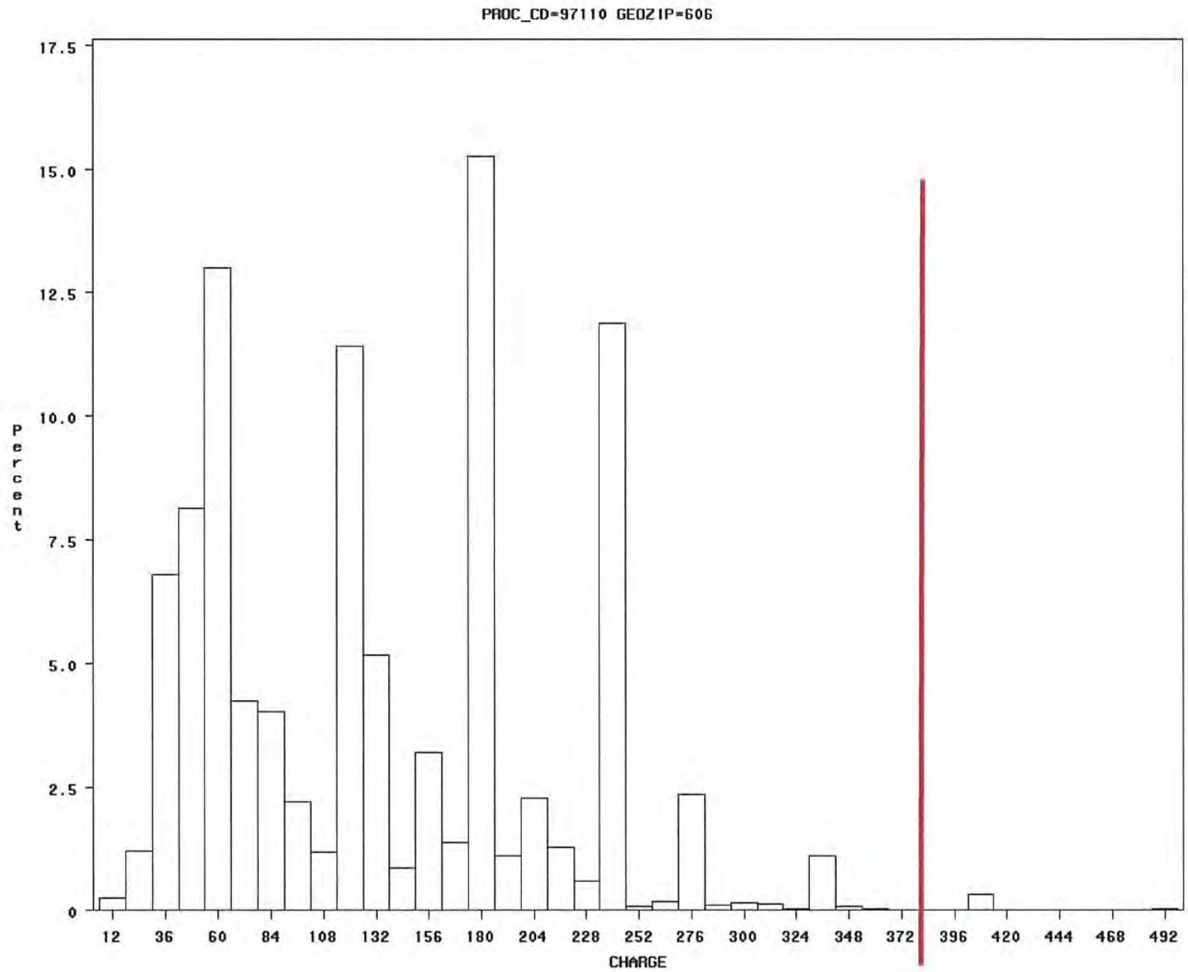
outliers, there is no reason to remove them from a distribution aimed at identifying the 80th percentile fairly and accurately.

Figure 3
CIGNA PPO Billed Charges for 2007: CPT 99213 / Geozip 117



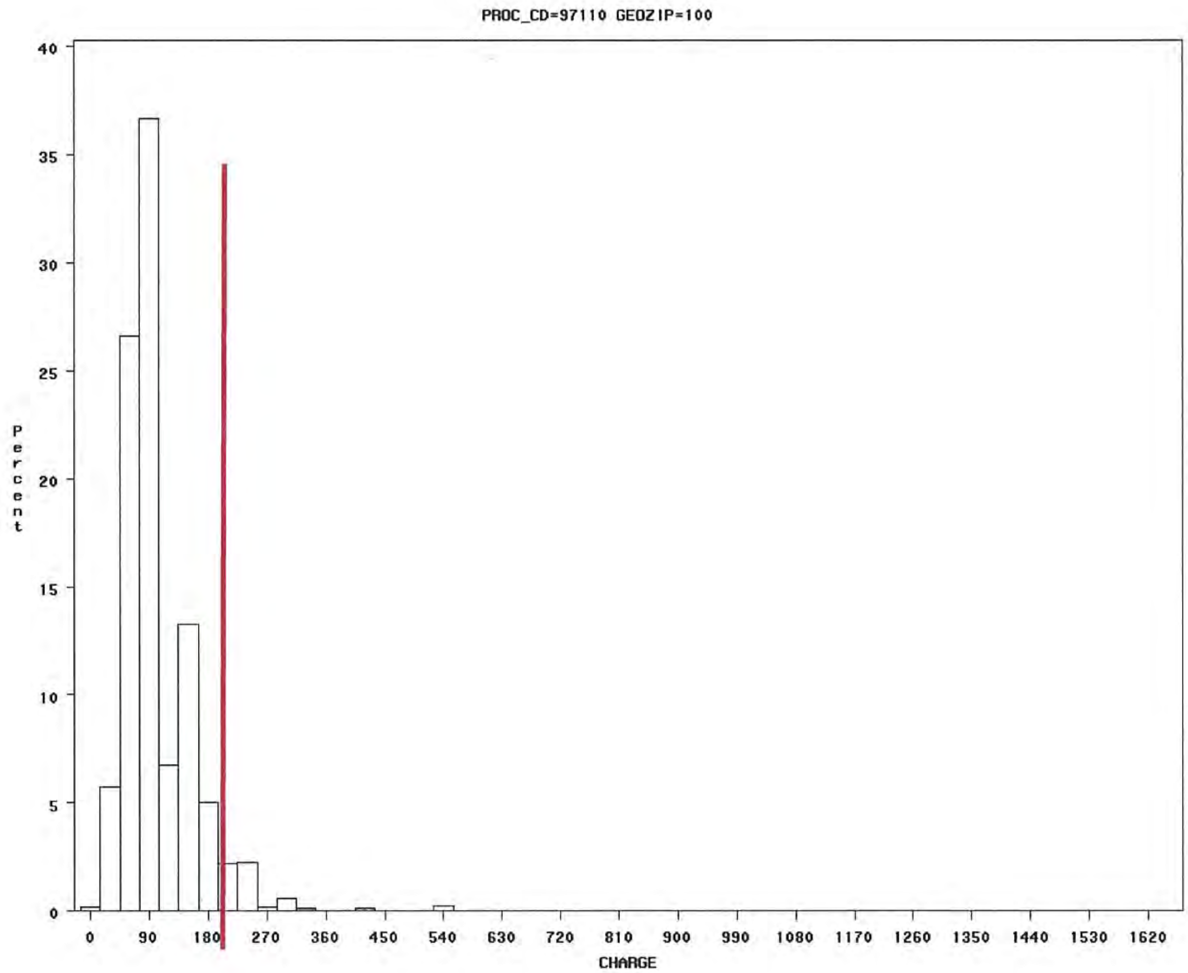
208. Figure 4 shows the distribution for CPT code 97110 (physical therapy) in geozip 606 (the Chicago western suburbs). This distribution is also unusual – with clusters of billed charges – peaks at \$60, \$120, \$180 and \$240 (\$276 and \$330 as well). All told, the distribution is skewed right, however. There are a few billed charges at \$400 and at \$500. Again, there is no indication that these are outliers at all. To use a high-low screen to screen out billed charges greater than \$375 would be neither advisable nor necessary. Even if the values in excess of \$375 are outliers they are part of the billed charge distribution and are appropriately considered in fixing the 80th percentile values.

Figure 4
CIGNA PPO Billed Charges for 2007: CPT 97110 / Geozip 606



209. Figure 5 illustrates the 2007 billed charge distribution for CPT Code 97110 in geozip 100 (Manhattan). This distribution is different although it is also skewed right. Here, the extreme value at $1620 may well be an outlier. The clusters of billed charges at $540, $400 and $300 while relatively expensive, are not. Once again, when determining the 80th percentile of billed charges there is no reason to remove any of these values. More importantly, to screen out billed charges over $120 as outliers (as the high-low screen would compel) is a clear mistake. Many of the screened charges are clearly not outliers. To remove them inappropriately reduces the 80th percentile value.

Figure 5
CIGNA PPO Billed Charges for 2007: CPT 97110 / Geozip 100



7. Conclusions regarding the high-low screen

210. In short, there is no scientific justification for the high-low screen. From an empirical standpoint, the high-low screen when applied to a right skewed distribution biases higher percentile values downward. Analysis using descriptive statistics shows how inappropriate elimination of data can bias percentile values downward. From a practical standpoint, when using percentiles to evaluate billed charges for UCR there is no justification for ignoring some billed charges merely because they are high if they provide grounds for a conclusion that the billed charges in question are reasonable.

C. Modifiers

211. Ingenix excludes some modifiers when it prepares the percentile data and includes others. For example, Ingenix excludes modifier 50, modifier 51 and modifier 52. It includes modifier "L" and "R" in the data as well as "many others."[71]

212. The Ingenix policy regarding outlier treatment is "ad hoc." It does not appear to have been scientifically based.

213. There are a wide range of modifiers that are used in connection with reimbursement for physician services. Some of them deal with "components" of the billed charge. For example, modifier 26 specifies the professional component and modifier TC the technical (equipment) component of a procedure, often in radiology. Empirical analysis of the Aetna data for 2007 shows the use of 840 different modifiers. The following table provides the most common modifiers that make up 95% of all modifier use in the Aetna data. The results are shown in Table 9.

Table 9
Common CPT Modifiers
Aetna ACAS Medical Claims Data from 2007

Modifier	Count	Percent	Description
26	17,893,120	33.8%	Professional component
25	9,048,767	17.1%	Separate proc same day
59	6,261,417	11.8%	Distinct
RT	2,606,078	4.9%	Right side of body
LT	2,444,042	4.6%	Left side of body
RR	1,955,565	3.7%	DME rental
90	1,304,763	2.5%	Reference lab
TC	1,296,627	2.4%	Technical component
NU	1,193,488	2.3%	New equipment
GP	1,072,828	2.0%	Occupational Ther
QW	970,230	1.8%	Waived test
51	727,770	1.4%	Multiple procedure
AA	448,812	0.8%	Anesthesia
50	388,778	0.7%	Bilateral procedures
RH	370,575	0.7%	Origin/Destination transport
76	272,772	0.5%	Repeat proc same physician
SG	266,048	0.5%	Amb Surg facility charge
52	236,041	0.4%	Reduced services
AT	233,238	0.4%	Paraprofessional
QX	197,844	0.4%	CRNA Service with direction
QK	182,500	0.3%	Medical direction 2-4 anesth

[71] Seare Depo. at 111:1-114:10.

57	167,984	0.3%	Initial decision surgery
79	167,524	0.3%	Unrelated proc same phys postop
24	162,620	0.3%	Unrelated EM surg post op
80	161,567	0.3%	Assistant surgeon
QZ	139,270	0.3%	CRNA without direction
91	137,382	0.3%	Repeat lab test same day
GA	132,537	94.9%	Advanced beneficiary notice

214. From a technical standpoint the billed charge should be constant for a given procedure even though a modifier is used. In theory, the modifier should not affect the billed charge and the payer should make appropriate adjustments relating to reimbursement. However, in practice, physicians alter their billed charges in response to the modifier. This can be ascertained from surveys with physicians or with the Aetna data, the CIGNA data and the contributor data.

215. In order to evaluate modifiers and billed charges we used Ingenix contributor data from 2006-2008 to conduct a preliminary study. A substantial of the billed charges in the contributor data had modifiers. The hypothesis that we tested was whether billed charges with modifiers were the same as billed charges without modifiers. We tested the impact of modifiers on the 80th percentile of billed charges for evaluation and management codes for existing patients, 99211-99215 and for seven common surgical procedures. The results are shown in Table 10.

Table 10
80th Percentile of Billed Charges With and Without Modifiers
Ingenix Contributor Data 2006-2008

			Include all modifiers	
CPT	**Occurrences**	**Mean**	**Median**	**80th**
99211	2,906,639	45.12	40.00	55.00
99212	9,565,446	68.01	64.00	80.00
99213	56,109,825	93.07	86.00	109.00
99214	28,178,585	141.13	130.00	168.00
99215	3,552,242	202.85	187.00	249.90
29881	138,144	3,702.69	2,810.00	5,000.00
43239	651,286	1,098.38	760.00	1,255.00
45378	737,803	1,166.04	900.00	1,402.25
45380	517,193	1,335.78	1,000.00	1,582.00
45385	347,667	1,508.87	1,200.00	1,782.00
59400	194,218	3,497.60	3,200.00	4,200.00
66984	374,103	2,415.96	2,250.00	3,300.00
			Exclude all modifiers	
CPT	**Occurrences**	**Mean**	**Median**	**80th**
99211	2,375,682	45.28	40.00	55.00
99212	7,934,919	68.17	64.00	80.00

99213	50,109,147	92.79	85.10	108.25
99214	24,853,127	140.86	130.00	167.00
99215	3,036,090	202.71	187.00	249.90
29881	63,252	3,992.83	2,912.00	5,446.00
43239	533,045	1,121.52	760.00	1,275.00
45378	681,253	1,149.71	898.00	1,388.00
45380	437,074	1,354.32	1,000.00	1,600.00
45385	314,379	1,479.02	1,200.00	1,735.00
59400	191,288	3,496.53	3,200.00	4,200.00
66984	98,931	2,818.70	2,400.00	3,986.00

216. The evaluation and management codes showed no difference with and without modifiers but modifiers substantially and significantly reduced billed charges for surgical procedures.[72] Accordingly, it is necessary to reject the hypothesis that modifiers do not affect billed charge and accept the alternative hypothesis that they do. It is possible that another source of downward bias in the Ingenix percentiles is related to the inclusion of billed charge data with modifiers.

217. Modifiers recognize that there are unusual circumstances that relate to a given medical procedure and provide for changes in payment based on the unusual circumstances. Examples include professional and technical components of a radiology procedure (modifiers PC and TC), increased levels of service (modifier 22) and reduced levels of service (modifier 52).

218. In theory, the impact of a modifier on physician payment should relate solely to the "allowed" amount rather than to the billed charge. The billed charge should be the same for a given procedure. The modifier changes the amount allowed and paid. In theory, it would be appropriate to include all billed charges when calculating percentile values. Since the modifiers should not affect the billed charges.

219. However, anecdotally, many physicians alter the amount that they bill based on the unusual circumstances. If this is the case, it would not be appropriate to include claims with modifiers when developing percentiles.

220. In order to test the hypothesis that modifiers do not impact billed charges we evaluated 55.2 million medical and surgical claims from the second month of the Ingenix contributor data for 2008. Nearly 8.6 million of the claims had payment modifiers, approximately 16%.

221. Nineteen of the modifiers (described in Table 11) were responsible for 8.2 million of the claims with modifiers or 95% of all of the modifiers.

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[72] The difference are significant at p=.01

Table 11
Common Modifiers and Frequency
(8.2 million of 8.6 million claims with modifiers)
Data: Ingenix contributor data – month 2 of 2008

Modifier	Description	Frequency
25	Separate physician service -- same day	2,853,565
26	Professional component	1,929,919
59	Distinct procedure or service	1,090,459
GP	Outpatient physical therapy	762,636
RT	Right side of body	202,371
LT	Left side of body	185,266
AT	Chiropractor service	171,727
90	Reference laboratory	170,911
TC	Technical component	161,947
51	Multiple procedures	141,128
52	Reduced service	73,778
GO	Occupational therapy	71,890
QW	CLIA waiver	60,777
24	Unrelated E&M same physician post op	58,331
57	Initial decision for surgery	53,697
GC	Resident under direction of physician	52,109
GA	Advance beneficiary approval	46,099
50	Bilateral procedure	42,115
76	Repeat the procedure same day same physician	40,046

222. For the 350 CPT's with the most claims we tested the mean billed charges for claims without modifiers and four claims with each of the 19 most common modifiers. Table 12 summarizes the results

Table 12
Modifier Impact on Billed Charges for Claims with Common Modifiers
Data: Ingenix contributor data – month 2 of 2008

Modifier	Avg % Diff	Abs Value
24	-0.4%	29.9%
25	27.1%	51.3%
26	-29.2%	44.9%
50	32.6%	58.0%
51	-3.9%	26.3%
52	-19.4%	34.5%
57	-2.7%	25.3%
59	-0.4%	17.5%
76	-13.5%	30.4%
90	-6.0%	29.4%

AT	-19.0%	32.8%
GA	-8.2%	27.8%
GC	0.7%	36.0%
GO	23.8%	55.3%
GP	26.5%	54.6%
LT	19.8%	40.7%
QW	-8.1%	30.8%
RT	14.4%	38.4%
TC	67.9%	90.6%
Average	1.9% (excl TC)	36.9% (excl TC)

223. We computed the average percent different for the mean billed charges for claims without and with modifiers by modifier and CPT. Table 12 contains an average of all of the results. Billed charges for some of the modifiers were within 10% of the billed charges without modifiers (modifiers 24, 51, 59, GC). For others billed charges with modifiers were greater than billed charges without (modifiers 25, 50, Geo, GP, LT, RT and TC). For others billed charges with modifiers or lack then billed charges without modifiers (modifiers 26, 52, 76, AP, GT and GW).

224. The technical component modifier raises billed charges substantially. Ingenix separately identifies TC and PC (professional component) modifiers and includes them in the percentile value tables. The overall average of the modifier effects is a 2% increase in billed charges for claims with modifiers (excluding the impact of the TC modifiers).[73] This suggests that we should accept the null hypothesis that modifiers do not impact billed charges.

225. This may suggest overall that it would be appropriate to leave claims with modifiers in the data when computing percentile values. However, closer scrutiny of the CPT modifier percent different matrix shows that most differences are either more than 10% higher or more than 10% lower and that these balance out on the overall. Thus, the modifiers increase billed charges for some CPT's and decrease billed charges in others -- but are rarely the same.

226. Accordingly, we computed the absolute value of the percent differences and averaged them by CPT and overall. As shown in Table 12, the average absolute value of the percent differences is substantial. Excluding modifier TC the difference is 37%. This suggests that even though the deviations balance on the whole, it would be inappropriate to include claims with modifiers at the CPT/geozip level. These findings suggest that the null hypothesis – that modifiers and do not impact of billed charges –

[73] Again, the number of claims suggests statistical significance of the average percent differences at p=.01.

should be rejected and that the alternative hypothesis, that they do impact of billed charges should be accepted.

227. As a result, the most appropriate treatment of claims with common modifiers would be to drop them when computing percentiles at the CPT/geozip level. To the extent that the PHCS data have included them, percentile values contained in the Ingenix products will be slightly higher than they would be otherwise.

228. In order to test the PHCS products for downward bias in one of the sections below we compare percentiles developed from the Ingenix contributor data to the PHCS product percentiles. In order to conduct the comparison we drop claims with modifiers. By dropping the modifiers any downward bias estimation of the PHCS product percentiles compared to the contributor data percentiles will be understated since the modifier elimination at will, overall, reduce contributor data percentiles by approximately 2%.

D. Use of Derived Data

229. By definition, derived percentiles do not reflect percentages for actual comparative billed charges in an area. They are an estimate or guess. In order to develop its MDR derivation Ingenix (1) develops a relative value for each CPT code, (2) divides the billed charges for a CPT code by the relative value to "normalize" the billed charges, (3) groups normalized billed charges from similar CPT codes together to find the percentile values for the normalized group, (4) multiplies the percentile values by the relative value factor to generate the derivation for each CPT code within the group.

230. There are scientific methods available to determine whether or not CPT codes belong to the same group based on distributions and other characteristics. Ingenix does not appear to have used these methods to generate the derivation groups. There are scientific methods available for generating relative values. Ingenix does not disclose how it develops relative values, only that the MDR relative values are generated "in house." Ingenix has investigated the relationship between the Medicare relative values and its relative values. It has not disclosed the results of this investigation.[74]

231. Ingenix also uses derived values for some CPT/GEO combinations in PHCS. However, the relative values used for the PHCS derivations are different from the MDR derivations. Again, Ingenix has not revealed the basis for the PHCS relative value units or reconciled differences between MDR and PHCS.

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[74] Gee Depo. II at 38:8-39:20.

232. As a result, percentile values supplied by Ingenix to health insurers specify different UCR values depending on which database is used. Ingenix has been questioned about the difference.[75] Some studies have shown that the difference may be in the order of ten percent.[76] Despite knowing about the discrepancies and having studied the different values produced by MDR and PHCS and despite internal pressure to "resolve" the products, (see INGENIXMDL000527453), Ingenix has not reconciled them, continues to use different relative value units and does not disclose the differences to customers or to the public.[77]

233. Neither defendants nor defendants' experts have attempted to investigate the impact of the derivations on the Ingenix percentiles or to justify the discrepancy between MDR and PHCS. No attempt appears to have been made to investigate the scientific accuracy or impact of the data derivation.

234. In order to study the effect of deriving values we used the 2007 CIGNA PPO data for evaluation and management codes 99211 through 99215 for all geozips. The hypothesis was that the derived 80th percentile values would be the same as the actual 80th percentile values. In the first step we calculated the actual 80th percentile value for each CPT / GEO combination. In the second step we used the MDR derivation methodology (using Medicare relative value weights since the Ingenix relative values were not available) to derive 80th percentile values for each combination. In the third step we compared the actual and the derived 80th percentiles for each CPT / GEO combination.

235. The MDR derivation algorithm divides billed charges for each transaction by the relative value for the derived charge in order to "normalize" the billed charges for the CPT code group. For purposes of evaluating the impact of combination we used Medicare relative value units.[78] Thus, we divided billed charges for 99211 by 0.53, 99212 by 1.08, 99213 by 1.82, 99214 by 2.73 and 99215 by 3.68. For each geozip the normalized billed charges were then arrayed in order to develop a combined 80th percentile.

236. Table 13 summarizes the results of the empirical using averages of the 80th percentile actual values and derived values by CPT code for all the geozips in the data. All differences are statistically significant at p=.01.

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[75] Gee Depo. II at 19:9-25:22.

[76] Gee Depo. II at 19:9-25:22.

[77] Gee Depo. II at 26:6-12..

[78] MDR uses an internal relative value unit that differs from Medicare.

- For CPT code 99211 in 21 of 887 geozips the derived 80th percentile was greater and in 866 geozips[79] the derived value was less. On average the actual 80th was $44.56 and the derived 80th was $28.99 – 35% lower.
- For CPT code 99212 the derived value was greater in 48 geozips and less in 832. On average the actual 80th was $68.65 and the derived value $59.08 – 14% lower.
- For CPT code 99213 the derived value was greater in 794 cases and less in 22. On average the actual 80th was $92.26 and the derived 80th $99.54, nearly eight percent higher.
- For CPT code 99214 the derived value was less in 133 cases and greater in 668 cases. On average the actual 80th was $141.53 and the derived 80th was $149.31, 5.5% higher.
- For CPT code 99215 the derived value was lower in 469 cases and higher in 415 cases. On average the actual value was $205.12 and the derived value $201.26, two percent lower.
- Overall the average of the actual 80th was $110.42 and the average of the derived 80th was $107.63 – an overall reduction, on average, of 2.5%.

Table 13
Actual 80th Percentile and Derived 80th Percentile
CIGNA 2007 PPO Data CPT Codes 99211-99215

CPT	Actual	Combined	Weight	Derived	Difference	Pct Diff	Derived Greater	Derived Less
99211	44.56	54.69	0.53	28.99	(15.58)	-35.0%	21	866
99212	68.65	54.69	1.08	59.07	(9.58)	-14.0%	48	832
99213	92.26	54.69	1.82	99.54	7.27	7.9%	794	22
99214	141.53	54.69	2.73	149.31	7.78	5.5%	668	133
99215	205.12	54.69	3.68	201.26	(3.86)	-1.9%	415	469
Overall	110.42			107.63	(2.79)	-2.5%	1950	2322

237. The analysis requires rejection of the hypothesis that the derivations produce the same percentiles as the actual data and acceptance of the null hypothesis, that the derivation process biases percentile values. The analysis shows that for more than half of the CPT / geozip combinations derived values are higher than actual, and for less than half of the CPT/geozip combinations the derived values are higher, with an overall downward bias. It may be argued that this means that to use actual rather

[79] Ingenix provides values for less than half of all geozips.

than derived values will produce "winners and losers." In truth, the derivation itself produces the winners and losers. To use actual values produces fair and accurate percentile values.

238. In only one-fourth of the combinations was the derived 80th percentile within 5% (plus or minus) of the actual 80th percentile.[80] Thus, the derivation produced an erroneous percentile value three-fourths of the time.

239. Most important, there is no scientific justification for the derivations. To the extent that actual 80th percentile values are available they should be used (if percentile values are justified for UCR at all). If actual 80th percentile values are not available, a different method for deriving values should be developed or a different method of determining UCR should be devised.

E. Small numbers issues

240. Ingenix reports percentile values for PHCS when there are nine or more observations. Seare Deposition. The Ingenix data are a sample, not a population. Accordingly, when Ingenix reports percentile values, a parameter, the scientific question is whether the percentiles reported are likely to reflect the population parameters or whether the values reported have occurred by accident or at random.

241. Another way to describe the question is whether the 80th percentile value reported by Ingenix for a CPT / geozip with nine billed charge observations is truly the 80th percentile – or whether it could be a data point in another percentile. The concept of confidence interval allows us to conclude, with a stated degree of probability, in what percentile range (confidence interval on either side of the observed parameter) the observed parameter (the sample 80th percentile) lays. (Urdan, 2005).

242. If we want to be sure that the 80th percentile we get from the sample is not the 75th or the 85th percentile, the confidence intervals cannot overlap. That is, the confidence intervals must be less than 2.5 percentiles either side of the 80th.

243. The greater the probability that the sample 80th is the same as the population 80th the less likelihood there will be for error. Statisticians often use a 95% chance that the observed equals the actual although it would be appropriate in a case involving payment to require greater, say 99% chance of accuracy and only one percent chance for error.

[80] The derivation methodology assumes that distributions for each of the CPT codes are the same within a geozip. If this is not the case derivation by normalizing and combining will generate the types of errors seen here.

244. Sample size calculation is straightforward.[81] It requires some information about the likely size of the population and decisions about the probability of success and error and the width of the confidence interval. Some examples illustrate the concept.[82]

a. Ingenix reports percentile values with nine observations. If there are only nine billed charges for the year in the CPT / geozip combination total, the nine observations will correctly report the percentiles since the observations are a population.

b. If there are ten billed charges and nine are reported. With a 95% probability the confidence interval will be nine. The actual percentile for the value reported would be expected to be between the 71st and the 89th percentiles. So the value reported for the 80th percentile could well be the 75th or the 85th percentile value.

c. If there are 100 billed charges for the CPT/geozip the confidence interval jumps to 25. The value reported for the 80th percentile could, in fact, lie between the 55th and the 100th percentiles.

d. Depending on the number of actual billed charges in a CPT / geozip, reporting percentiles with nine observations will produce erroneous "true" percentile values most of the time.

245. If we require confidence intervals of 2.4 so the 80th does not overlap with the 75th or the 85th, and if we would like to say with 95% confidence that the 80th percentile reported is the true 80th for the population of billed charges, and if there are 300 billed charges for the CPT / geozip combination during the year, we will need 254 observations for accuracy, far greater than the nine reported by Ingenix.

246. Ingenix has itself recognized this problem. Internal studies of the reporting issue have recommended reporting percentiles only when there are 50 or more data points, although this observation was made as a bootstrapping study rather than scientific degree of confidence. Ingenix has also commissioned expert studies of the issue that have not been made public.[83]

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[81] There are online versions. See http://www.surveysystem.com/sscalc.htm.

[82] Assuming a normal distribution which physician billed charges are not. A distribution skewed right will require even more observations in the sample.

[83] Seare Depo. at 64:8-65:13.

247. We developed 80th percentile values for 300 common CPT codes for 100 of the most populous geozips using Ingenix Contributor data from 2007 for comparison with 80th percentile values from the PHCS products for 2007 version 1, 2007 version 2 and 2008 version 3.

248. We extracted CPT / geozip combinations form this analysis for which only nine claims have been reported. Table 14 contains the results.

Table 14
Ingenix PHCS Product: 80th Percentile Values for Which 9 Claims Are Used to Report

Geo/Cpt	Rel 07.1	Rel 07.2	Rel 07.3
050-84100	11	31	35
050-88307	200	235	307
054-72110	225	225	225
132-77003	250	250	250
140-86900	21	26	22
140-88307	107	146	107
147-82565	20	20	20
152-77057	104	145	200
169-84403	55	55	55
193-71010	85	85	67
275-77080	332	450	400
287-77080	300	265	265
287-92226	59	65	65
321-86703	50	22	85
321-88307	370	408	370
546-77052	44	44	47
553-77052	41	38	38
558-92226	100	100	73
558-94760	32	32	32
560-77080	420	338	290
571-99173	34	34	14
631-77051	40	40	50
647-82670	97	157	163
647-85730	30	40	40
647-90767	74	74	74
647-93971	250	231	231
654-97002	60	60	84
723-90649	168	168	150
999-73620	119	104	114
999-80050	123	392	392
999-82565	41	53	61
999-99285	431	452	648

249. There is large variation in the 80th percentile values from one PHCS product release to another. There are many large increases and large declines – over six month intervals. There is no justification, for example, for the UCR for CPT 77080 in geozip 275 to be $332 in June 2007, $450 in July of 2007 and $400. There is no scientific justification for reporting percentile values with as few as nine observations. There is no practical justification for it as well.

F. Provider qualifications

250. The Ingenix PHCS percentiles do not differentiate billed charge percentiles by provider qualification and training. The hypothesis on which this is based theorizes that different types of providers and specialties within a provider type do not bill at different levels and that the market does not differentiate based on training and experience so that it is appropriate for Ingenix percentiles (and for UCR payment based on them) to ignore provider qualifications and training.

251. It is possible to test this hypothesis using CIGNA data, Aetna data and contributor data.

G. Use of geozips for the community / product market

252. UCR specifies reimbursement for usual, customary and reasonable charges for the same or similar services in the community. The geozip is not a community. It bears no relationship to a geographic market.

253. By using percentile data compiled in geozips for UCR there is no real reference community or market for a comparison. The real reason for use the geozip is as a convenience for purposes of developing a percentile system for reimbursement. The geozip has been used for aggregation of data without any scientific exploration of the appropriateness of the aggregation or its impact.

254. Defendants use the geozip for convenience since the zip code is available for place of service from the physician's zip code[84] and because there are persistent concerns about having enough data to provide meaningful percentile distributions so that combining geographic locales at the geozip level provides more distributions with meaningful information.

[84] Although there is the potential for error when the physician's place of service differs from the billing office and the zip for the billing office is used for the place of service.

255. Defendants' experts justify the Ingenix use of the geozip in the same way that they justify failure to deal with provider qualifications and training:

- Proper identification of the community or geographic market rather than use of the geozip will create "winners and losers."
- Use of smaller geographic areas will disaggregate the data in such a way that renders it unusable.

256. The premise here is that the status quo must be maintained because there is no appropriate statistical and legal remedy for it. This approach has two major flaws. First, it perpetuates a system that itself has provided distortions that create winners and losers.[85] Second, there are ways to do better.

257. In order to illustrate the impact of the geozip distortion we use CIGNA's 2007 PPO data to compare the 80th percentile of billed charges for evaluation and management services for CPT 99213 (intermediate office visits) among the various zip codes within geozip 601 – the western suburbs of Chicago. Figure 6 shows the geographic area included in geozip 601.

258. Table 15 shows the 80th percentile of physician billed charges for the zip codes in geozip 601 and the 80th percentile for the billed charges at the geozip level. Without the high-low screen the 80th percentile for the geozip is $114. With it, the 80th percentile is $111. For 56 zip codes (75%) the 80th percentile value exceeds the geozip 80th percentile values, in most cases by a substantial amount.[86] For 18 zip codes (25%) the pooling increases the 80th percentile level. Thus, the geozip created "winners" and "losers" but many more losers than winners.

[85] Somehow it is appropriate for the geozip system to create winners and losers but it is not appropriate to fix the problem.

[86] For two of the zip codes, 60116 and 60161, the 80th percentile values are $1200 and $1170 respectively. The result of the use of the geozip is a very large reduction in reimbursement. While it is possible these are outliers or mistakes, it is equally possible that the values represent unique medical care services provided in a teaching hospital setting. They should be investigated, not automatically eliminated.

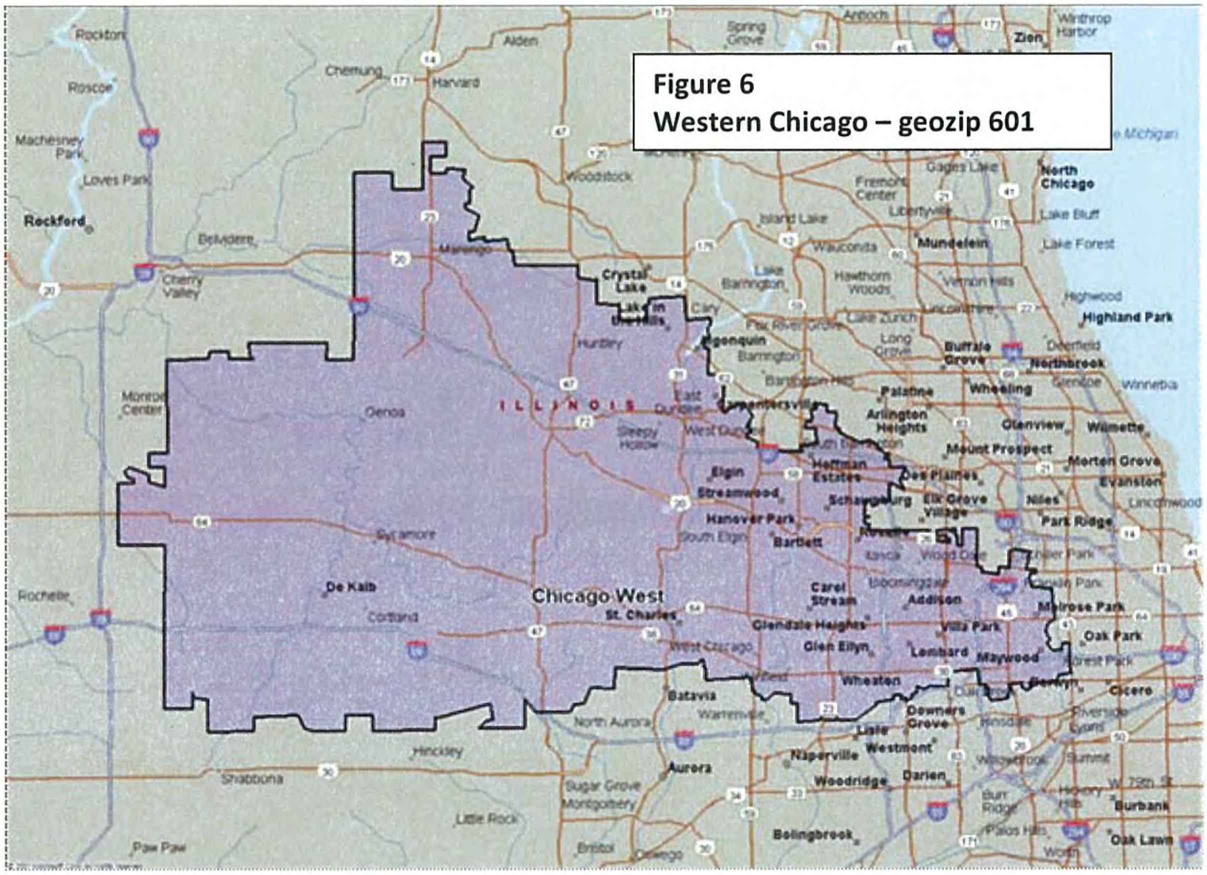


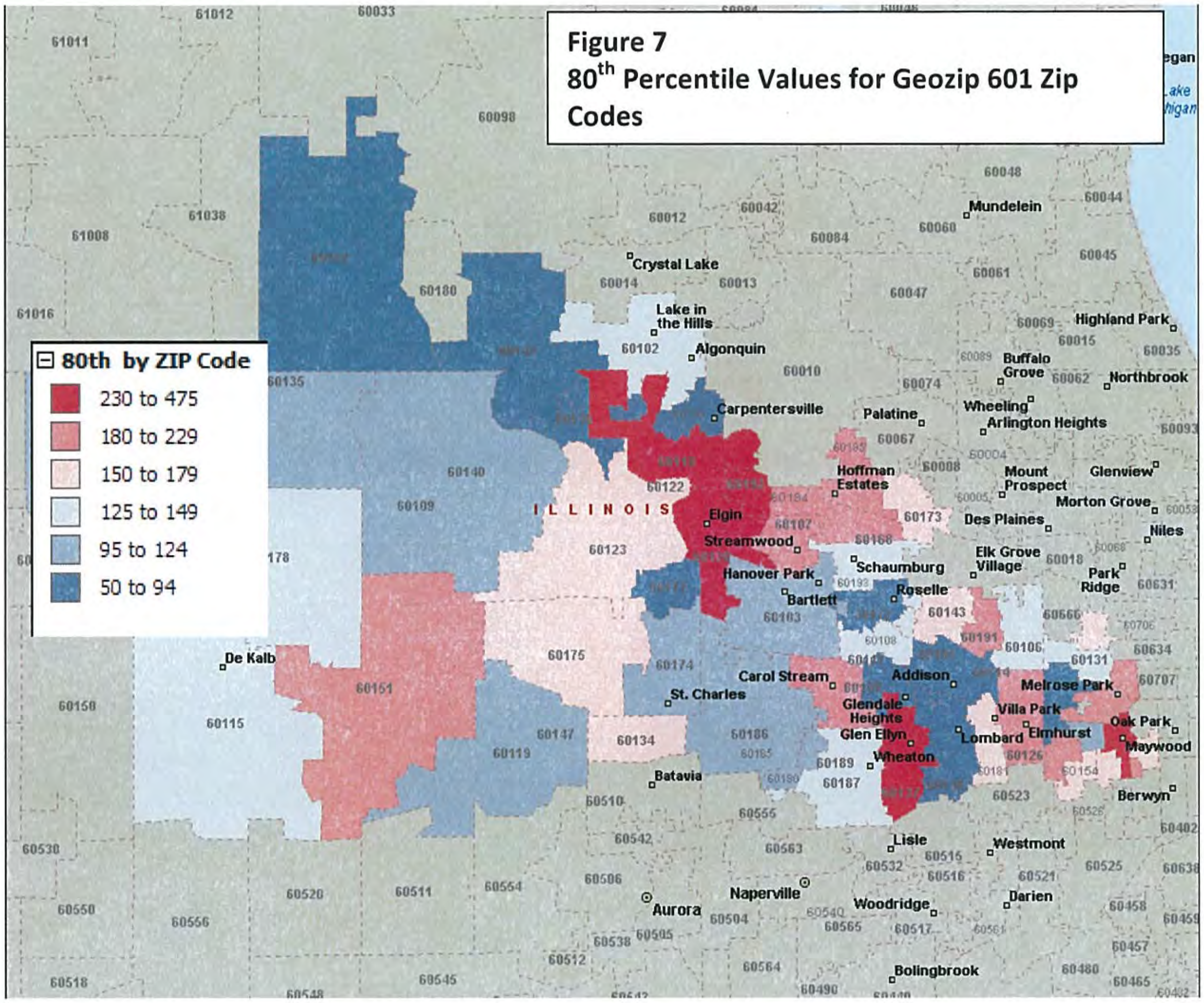
Figure 6
Western Chicago – geozip 601

Table 15
Comparison of 80th Percentile of Billed Charges at the Zip Code Level
For CPT 99213 in Geozip 601

ZIP	80th	ZIP	80th
60116	1,200.00	60130	150.00
60161	1,170.00	60187	148.00
60121	950.00	60167	148.00
60118	475.00	60131	148.00
60109	410.00	60157	140.00
60132	399.00	60193	138.00
60153	340.00	60108	135.00
60192	325.00	60178	134.00
60199	280.00	60102	131.00
60169	275.75	60106	130.00
60168	265.00	60115	127.00
60120	250.00	60124	125.00
60137	237.00	60174	123.00
60194	225.00	60103	122.00
60160	225.00	60189	120.00
60151	210.00	60104	115.49
60141	200.92	60185	115.00

60197	200.00	60138	115.00
60159	200.00	Geozip No screen	114.00
60126	196.00	Geozip with screen	111.00
60107	191.21	60122	110.00
60191	188.00	60190	107.02
60195	183.00	60146	105.00
60188	180.00	60119	105.00
60171	180.00	60140	95.00
60162	180.00	60135	95.00
60181	175.00	60101	92.00
60175	175.00	60177	90.00
60173	175.00	60172	90.00
60155	175.00	60152	90.00
60133	175.00	60142	90.00
60123	175.00	60110	84.00
60156	172.00	60147	79.74
60143	166.50	60163	70.00
60154	160.00	60139	65.00
60176	154.00	60148	63.00
60186	150.00	60164	55.00
60134	150.00	60136	50.64

259. Figure 7 maps the 80th percentile values to the zip codes in geozip 601. The zip codes



with high billed charges are in red and those with low billed charges are in blue. Generally, the red areas have 80th percentile billed charges higher than the geozip 80th and the blue areas have billed charge percentiles lower than the geozip 80th. There does not appear to be any particular pattern to the 80th percentile levels although to the extent that the 80th percentile of billed charges is similar in zip code groupings the patterns may suggest the existence of geographic markets

260. The zip code is not a particularly useful estimate for a geographic market. The essence of a geographic market is the distance to which patients will travel for physician care. The zip code, like the geozip, is a post office construct. What this analysis shows is that the geozip is not a useful

surrogate for a geographic market or for a "community" for UCR. A -more meaningful geographic market estimation is needed if the use of percentiles for UCR is to have any meaning.

H. The effect of billed charge inflation over time on percentiles

261. In order to provide a "current" product, Ingenix updates MDR four times per year and incorporates an inflation multiplier cased on the consumer price index.[87] The PHCS product is updated two times per year but does not use an inflation multiplier.[88]

262. As noted above, data collection, processing of percentiles and implementation of the percentile data for UCR adjudication can produce a lag of more than two years. The health insurers do not apply an inflation factor when using the percentiles to educate UCR and the products themselves do not provide an inflation factor. In effect, Ingenix and health insurers hypothesized that billed charge inflation does not impact percentile values or the UCR is that are determined using them.

263. In order to test the hypothesis that billed charge inflation as little influence on percentile values or UCR, we look at billed charge inflation in the Ingenix contributor data, in the Aetna medical data and in the CIGNA PPO data.

264. The Ingenix products themselves illustrate the influence of billed charge inflation. In the study of the 300 CPT codes in 100 geozip areas referenced above we compared 80th percentile values for the combinations in the 2007 contributor data with the Ingenix products for the first release of 2007, the second release of 2007 and the first release of 2008.

265. The average 80th percentile value for these 30,000 CPT/geozip combinations was $181.81 for the first release of 2007, $185.02 for the second release of 2007 and $185.42 for the first release of 2008. Billed charge inflation in the Ingenix product percentiles for the 80th percentile was 1.8% between the first release of 2007 and the second, and 2% between the first release of 2007 and the first release of 2008. The differences are statistically significant at p=.01. And, as noted above, the high-low screen used by Ingenix acts to minimize billed charge inflation. These findings suggest rejection of the hypothesis that billed charge inflation does not influence percentile values and their use in UCR. If billed charge inflation is 2% per year, a two-year lag in implementing percentiles for UCR suggests that the percentile values may be biased downward by as much as four percent when the lag time frame is two years.

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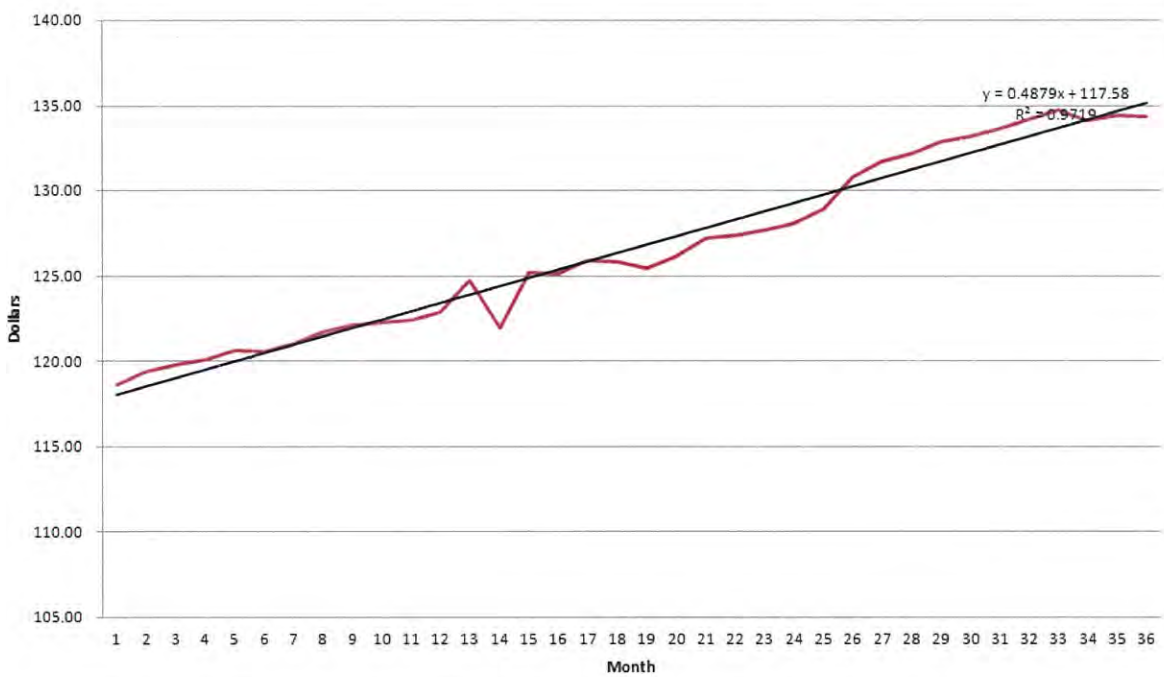
[87] INGENIXMDL000950390

[88] *Id.*

266. We also used the Ingenix contributor data itself to evaluate billed charge inflation over time. We looked at the 80th percentile values nationally for the contributor data for the 100 most common CPT codes in the Ingenix data. The results are set forth in Data Appendix 2. Figure 8 illustrates the trends graphically.

267. There is a clear, strong, statistically significant linear trend in the Ingenix data month by month. Fitting a line to the data explains 97% of the time trend variance. The slope of the line is one half. In terms of the overall average, 80th percentile billed charge values for the 80 most common CPT codes increase at the rate of about six dollars per year, between four and five percent. The coefficient for the slope is a statistically significant at p=.01.

Figure 8
100 Most Common CPT Codes - Average 80th Percentile Nationally
Ingenix Contributor Data by Month
January 2006 (month 1) to December 2008 (month 36)



268. Once again, the data require rejection of the hypothesis that the effect of billed charge inflation on percentile values is minimal or nonexistent, and acceptance of the null hypothesis, that billed charge inflation affects billed charge percentiles.

269. Indeed, these findings provide additional support for the conjecture that the high-low screen provides a downward bias to billed charge inflation since the billed charge 80th percentile

inflation in the Ingenix contributor data without the high-low screen is four to five percent a year while the inflation rate contained in the Ingenix products compiled with the high-low screen is two percent.

270. Moreover, the studies described above of inflation rates of billed and allowed charges over time in the Aetna data and the CIGNA data also show strong inflationary trends in billed charges over time that are not consistent with the Ingenix products.

271. The overall average 80th percentile of billed charges for the 50 most common CPT codes in the CIGNA data increased from $135.30 in 2001 to $242.54 in 2008, an increase 80%, 10% per year.

272. The overall average 80th percentile of billed charges for the 50 most common CPT codes in the Aetna data increased from $71.81 in 2001 to $97.56 in 2008, an increase of 36% or 5% per year.

273. In short, if the Ingenix percentile products correctly report current period percentiles they should incorporate billed charge inflation as reflected in the contributor data and if health insurers properly implement percentile data for use in UCR, they too should incorporate appropriate inflation factors.[89]

VII. Accurate percentiles and bias in the PHCS data

274. Given the Ingenix issues, the crucial question becomes the level of influence, if any, that these issues had on the percentile data contained in the Ingenix products.

275. Defendants' experts provided reports during class certification that compared the Ingenix products to a wide range of external data including billed charge data from CIGNA and United, physician fee reference software and Medicare claim averages. They reached conclusions that the percentiles in the Ingenix data were not biased downward because comparisons to these references did not show bias.[90]

276. The scientific design of those comparisons presupposed that the external references were reflective of the population of billed charges (required for the external reference to constitute a "standard") or that they consisted of representative samples of billed charges (or at least were the same as the Ingenix data) that had been produced without the Ingenix issues. Neither of these presumptions is supported scientifically. The reference data did not constitute the population of billed charges and the data compilations for them are unknown and likely, every bit as problematic as Ingenix.

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[89] These factors could be developed in the aggregate or at the geozip level.

[90] Actually, a number of the comparisons did show downward bias.

277. The only way to determine whether the lack of representativeness of the Ingenix data biases billed charge percentiles downward is to obtain the population of billed charge data to compare the percentiles in the population to the percentiles in the Ingenix sample. The population of billed charges is not currently available so no scientific investigation of bias due to lack of representativeness can be made. As noted above, estimates are possible using the Ingenix contributor data.

278. To evaluate the effect of the Ingenix issues (apart from representativeness), we used Ingenix contributor data described above to construct billed charge percentiles free from the questionable techniques: without the high-low screen, without modifiers, in current time, with enough data to report values and without derivations. We then compared the contributor data billed charge percentiles to the percentiles contained in the products distributed by Ingenix. Since the PHCS percentiles were built from the contributor data the hypothesis The hypothesis for the study was that there would be no difference between the contributor data

279. We used the Ingenix contributor data from 2006 to 2008 (all of the contributor data that was available) for the analysis to generate comparison billed charge percentiles. Due to data, time and resource constraints the primary focus of the comparison was medical and surgical procedures and dental procedures.

280. The Ingenix product data are a series of text files, representing a release specified by Ingenix. PHCS is updated twice each year, in May and in November. The PHCS product files include medical, dental, HCPCS.[91] The files used were the Ingenix "AC/DC" files, which contained the largest volume of code/geozips combinations. This consisted of procedure codes arrayed by geozips (421 for 2006, 448 for 2007 and 475 for 2008).

281. The PHCS product records include procedure code, the total claim counts used to derive the data, the mean, the median and a series of percentile rankings:

- 60th
- 70th
- 75th
- 80th
- 85th
- 90th
- 95th percentile

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[91] There are inpatient products and anesthesia products. Time and resource constraints did not permit evaluation of them.

282. There is an additional field in the PHCS product that contains coded information regarding the methodology used to calculate or derive the UCRs. As noted above, any code/geozip combination with less than nine data points (claim lines) used derivations to generate billed charges.[92]

283. The contributor data set consisted of a series of 10 to 12 flat-file text files for each year. The 2006 and 2008 files contained 12 monthly submissions. The 2007 consisted of ten unequal files. Each record within the files contains procedure codes, zip code, billed charge, allowed amounts (although many allowed amounts are not provided), diagnosis codes, type of service and place of service, modifiers, service dates and other information.[93]

284. Contributor data for calendar years 2006, 2007 and 2008 represents a total of approximately 4.2 billion claim lines distributed as follows:

- 2006 – 1.428 billion
- 2007 – 1.239 billion
- 2008 – 1.535 billion

285. With some variation from year to year, there were approximately 125 payers that contributed data. However, as noted above, four firms account for nearly 60% of the data contributed and 10 firms contributed 70%.

286. There are 11.4 million unique provider keys reported, however, each payer has its own method for developing an ID, so it is not possible to determine the number of providers who were represented in the contributor data.

287. In order to increase the reliability of results we conducted two independent studies of the contributor data, one using Minitab software and a second using SAS (Statistical Applications Software). Both are accepted software platforms that are commonly used by statisticians and econometricians.[94]

288. The first study developed percentile values for the 300 most common procedure codes in 300 geozip areas selected at random (the 300 CPT study).[95] The 300 CPT study included primarily

[92] The derivations produce nonsensical results. For example, the PHCS product may show zero for the median value yet provide 80th percentile values.

[93] A large number of records contained negative units with an associated negative charge value. Ingenix drops the negatives when it processes claims. Some records also contain multiple units. A field called 'New Units', converts multiple units for the claim line..

[94] Microsoft SQL and Microsoft Excel were also used to process and summarize results.

[95] Mr. Frank Cohen provided statistical services for major portions of the 300 CPT study.

medical and surgical codes although a number of dental codes were included. Thus, the 300 CPT study included comparisons of 90,000 CPT / geozip combinations representing more than half of the data points.

289. The 90,000 combinations used half of the contributor data in 2006, 56% in 2007 and 65% in 2008. Since the study focused on medical surgical and dental claims its comparisons used much more than half of the contributor data. By comparison, the PHCS percentiles for the same CPT / geozip combinations were developed using fewer claims lines. The results are found in Table 16.

Table 16
Claim Lines Used for 300 CPT Study Comparisons

Year	Study claim lines	Contributor Total	Percent	PHCS lines prior	PHCS lines current	% prior	% current
2006	955,014,114	1,427,958,610	66.88%	486,960,660	406,529,222	34.10%	28.47%
2007	1,030,250,008	1,239,153,599	83.14%	501,664,894	505,428,680	40.48%	40.79%
2008	840,345,981	1,535,210,117	54.74%	676,609,221	709,122,755	44.07%	46.19%

290. The second study (the 350 CPT study) was conducted to verify and expand the first. It included the 350 most common 350 codes since they represent 90% of the claims lines and 450 most common geozips with the most claims since these geozips represent 90% of the claims.[96] The 350 CPT study evaluated CPT / geozip combinations for 80% of all contributed claims. The 350 CPT study evaluated more than 900 million claims for 2006 and 2007 and 1.3 million for 2008.

291. Both studies produced the following parameters for each CPT / geozip combination:

- Claims line count for contributor data and for PHCS percentiles
- Mean, median, 60th, 70th, 75th, 80th, 85th, 90th and 95th percentiles for PHCS and for contributor data

292. A number of claims had billed charge values of zero or very small amounts ($0.01 for example). Many claims had negative values. In accordance with Ingenix policy we eliminated claims with negative values, zero values and values less than $1 for billed charges.

293. The PHCS products are released two times per year, in May and November. They are built using a "rolling" one year data collection time frame with the cutoff date one month prior to product release. Thus, in the best case – if health insurers adopt the new release within one month - the November product will be used for adjudication during the first six months of the following year and the May product will be used for adjudications for the last six months of the year.

[96] For 2008 in order to expand the study even broader the 350 CPT codes were used and all geozips in the contributor data were included.

294. UCR pertains to comparisons of contemporaneous billed charges, not billed charges from six to eighteen months prior. Accordingly in an effort to make a similar contemporaneous comparison we compare the contributor billed charges for a given year or six month time frame to the immediately preceding PHCS product, and also to the contemporaneous product. For example, we compare the contributor 2006 billed charge percentiles to the November 2005 PHCS release (2005 Version 2) and to the May 2006 billed charge percentiles (2006 Version 1) since these are the products that are used to adjudicate the 2006 claims.

295. As noted above, many modifiers impact billed charges. The Ingenix modifier policy is fairly involved and results in the inclusion of a number of claims with modifiers in building the PHCS percentiles. Because so many modifiers change billing behavior, we drop claims with modifiers in constructing the percentile values for the comparison data.

296. For each CPT/geozip combination. We calculate the difference between the equivalent percentile values by subtracting the PHCS product value from the contributor data value. We then computed a percent difference, the difference divided by the PHCS product value. For overall analysis we developed overall percent differences weighted by the number of claims lines for the particular CPT/geozip combination. We also considered the number and proportion of occurrences, where the contributor data percentile was greater than the PHCS product percentile, the number and proportion of occurrences, where they were equal and the number and proportion of occurrences, where the contributor data percentiles were less than the PHCS percentiles.

297. In accordance with the discussion concerning the number of data points required for reporting percentiles with confidence, we limited our comparison to CPT/geozip combinations with 255 or more claims.

298. In order to assess the impact of the number of claims on the comparison we evaluated the difference, the percent difference and the variance of the percent difference related to the number of claims in the contributor data and the PHCS percentiles. We used 2007 contributor data from the 350 CPT Study with number of claims (Claims), average value of billed charges (Avg Chg), differences (Diff), percent differences (% Diff) and variances (Var) for comparison with the second release of PHCS for 2006 (V2) and the first release of 2007 (V1). The analysis focused on the 80th percentile and the 90th percentile (which represent more than 65% of percentile levels used to adjudicate UCR claims).[97]

[97] Percentile distributions reflected in the Aetna claims data.

299. The results of the correlation analysis for the contributor claims are set forth in Tables 17 and 18.[98] Average billed charge dropped as the number of claims increased. More expensive claims are less frequent than those less expensive. Differences between contributor data percentiles and the PHCS percentiles increased as claim size increased both as an absolute amount and as a percentage.[99] As the average charge increased the differences and percent differences between the contributor percentiles and the PHCS percentiles increased. The differences between the contributor data 80th and 90th percentiles and the PHCS 80th and 90th percentiles dropped as the number of claims increased. The percent differences also dropped with the number of claims as did the variance. This suggests that the differences and percent differences would be even greater if we included comparisons for CPT/geozip combinations with less than 255 claims. The increasing variance indicates that the reliability of the comparisons (and the percentile values themselves) drops as the number of claims increases.

Table 17
Correlation of CPT/Geozip Claim Numbers, Differences, Percent Differences and Variances
Contributor and PHCS Percentile Values for 80th Percentile
Contributor Claims
(Pearson Correlation Coefficients)

	Claims	Avg Chg	Diff V1	Diff V2	%Diff V2	% Diff V1	Var V1	Var V2
Claims	1.000	-.026**	-.033**	-.033**	-.053**	-.045**	-.008*	-.008*
Avg Chg	-.026**	1.000	.963**	.961**	.642**	.582**	.641**	.641**
Diff V1	-.033**	.963**	1.000	.999**	.709**	.643**	.693**	.694**
Diff V2	-.033**	.961**	.999**	1.000	.710**	.642**	.692**	.693**
% Diff V2	-.053**	.642**	.709**	.710**	1.000	.911**	.426**	.428**
% Diff V1	-.045**	.582**	.643**	.642**	.911**	1.000	.423**	.423**
Var V1	-.008*	.641**	.693**	.692**	.426**	.423**	1.000	1.000**
Var V2	-.008*	.641**	.694**	.693**	.428**	.423**	1.000**	1.000

**** indicates statistical significance at p=.01**

[98] The results are the same for the PHCS claims for release 2 of 2006 and release 1 of 2007.

[99] Indicative possibly, of the impact of the high-low screen.

Table 18
Correlation of CPT/Geozip Claim Numbers, Differences, Percent Differences and Variances
Contributor and PHCS Percentile Values for 80th Percentile
Contributor Claims
(Pearson Correlation Coefficients)

	Claims	Avg Chg	Diff V1	Diff V2	%Diff V2	% Diff V1	Var V1	Var V2
Claims	1.000	-.025**	-.030**	-.030**	-.046**	-.047**	-.008*	-.008*
Avg Chg	-.025**	1.000	.978**	.977**	.610**	.617**	.767**	.768**
Diff V1	-.030**	.978**	1.000	.999**	.661**	.656**	.563**	.806**
Diff V2	-.030**	.977**	.999**	1.000	.661**	.654**	.565**	.807**
% Diff V2	-.046**	.610**	.661**	.661**	1.000	.922**	.356**	.487**
% Diff V1	-.047**	.617**	.656**	.654**	.922**	1.000	.316**	.465**
Var V1	-.008*	.767**	.806**	.807**	.486**	.462**	.673**	1.000**
Var V2	-.008*	.768**	.806**	.807**	.487**	.465**	.669**	1.000

**** indicates statistical significance at p=.01**

300. We also used the 2007 350 CPT study of the contributor percentile – PHCS differences to perform a simple linear regression assessing the impact of claim numbers and average billed charge levels on the differences (weighted average percent difference) between the contributor percentiles and the PHCS percentiles. The regression is predictive (F value of 31,201 significant at p=.01) and explains a good portion of the variance (adjusted R square = 0.414). Model coefficients are significant at p=.01. The number of claims is negatively associated with the average weighted percent difference. The percent difference declines as the number of claims increases. The level of the billed charges is positively associated with the percent difference. As the billed charge amounts increase the percent differences increase. Once again, as the number of claims decreases the percent difference between the contributor data percentiles and the PHCS percentiles increases. If we were to include CPT / geozip combinations with between nine and 255 claims the differences found by the studies would increase.

A. The 300 CPT Study

301. Table 19 summarizes the results of the 300 CPT for overall comparisons. Table 20 summarizes the results for medical and surgical claims and Table 21 summarizes the results for dental claims. The lines labeled "Avg Diff" is the average of the difference between the contributor data

percentile and the PHCS percentile for all of the CPT/geozip combinations for which comparisons were available. The "Wtd avg % diff" is the weighted average percent difference for all of the comparisons.

Table 19
Summary of Comparisons of Contributor Data Percentiles and PHCS Percentiles
300 CPT Study - Overall Comparisons

Contributor	Ingenix	Percentile	50	60	70	75	80	85	90	95
2006	**2005_2**	Avg diff	6.70	10.04	14.70	17.80	22.37	29.10	40.07	61.44
		Wtd avg % diff	8.3%	9.5%	11.4%	12.6%	14.1%	16.4%	20.3%	29.3%
	Claims	955,014,114								
	Comparisons	76,011								
2006	**2006_1**	Avg diff	3.58	7.25	12.54	15.99	21.10	28.82	41.51	66.88
		Wtd avg % diff	6.1%	7.6%	10.0%	11.4%	13.3%	16.2%	21.0%	31.1%
	Claims	773,985,790								
	Comparisons	67,977								
2007	**2006_2**	Avg diff	15.32	20.38	27.67	33.21	41.34	52.32	69.16	100.74
		Wtd avg % diff	13.4%	15.7%	19.1%	21.1%	24.2%	28.9%	36.2%	55.4%
	Claims	724,351,715								
	Comparisons	63,196								
2007	**2007_1**	Avg diff	13.60	18.13	24.71	29.47	36.47	45.96	60.19	87.99
		Wtd avg % diff	12.6%	14.7%	17.5%	19.2%	21.7%	25.3%	31.1%	46.2%
	Claims	1,010,517,478								
	Comparisons	78,096								
2008	**2007_2**	Avg diff	11.19	15.53	21.85	26.41	33.23	42.46	56.69	84.02
		Wtd avg % diff	14.5%	17.1%	20.6%	22.9%	25.6%	30.4%	38.0%	57.0%
	Claims	1,011,930,853								
	Comparisons	78,394								
2008	**2008_1**	Avg diff	8.67	12.90	19.00	23.51	30.18	39.46	53.49	81.04
		Wtd avg % diff	12.5%	14.9%	18.5%	20.7%	23.8%	38.8%	64.3%	119.0%
	Claims	1,039,900,755								
	Comparisons	81,436								

1. Overall comparisons

302. The number of claims used for the that comparison was substantial: 955 million for the comparison of 2006 contributor data with the November 2005 PHCS release, 724 million for the comparison of 2007 contributor data with the November 2006 PHCS release and 1 billion for the comparison of the 2008 contributor data with the November 2007 PHCS release. As a result of the number of claims and the number of comparison combinations all of the summary comparisons are statistically significant at p=.01.

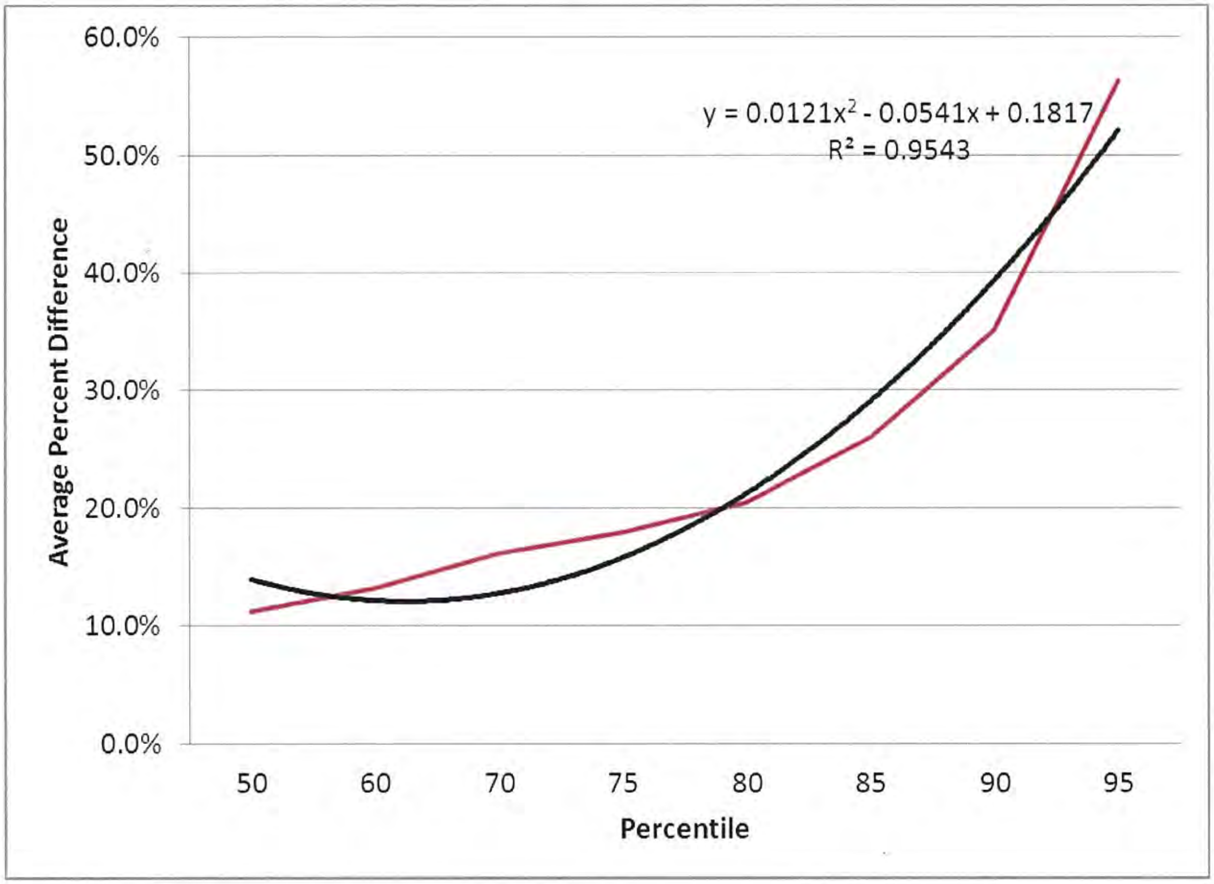
303. The number of CPT/geozip combinations in the final analysis was less than 90,000. After eliminating combinations without PHCS values and with PHCS values of zero for one of the percentiles in the tables and after eliminating combinations with fewer than 255 claims, the number of combinations evaluated ranged from 63,000 for the comparison of the 2007 contributor data with the second PHCS

release of 2006, to 81,436 at the comparison of the 2008 contributor data with the first release of 2008 PHCS. Despite the eliminations the evaluations encompassed the great majority of contributed data.

304. Overall, the contributor percentile values measured both by average differences and weighted average percent differences were consistently and substantially greater than the PHCS equivalents at each percentile level. On average all contributor differences and percent differences were positive – the contributor values are always greater than the corresponding PHCS values. The differences are all statistically significant at p=.01. Accordingly, the hypothesis, that the Ingenix processing had no impact on percentile values, is rejected and the alternative hypothesis, that the Ingenix processing altered percentile values is accepted. The direction of the processing bias is markedly downward. The Ingenix processing creates a downward bias.

305. As shown in Figure 9, the overall average weighted percent differences increase geometrically as the percentile levels increase. The relationship closely fits a quadratic curve. This may well reflect the impact of the high-low screen on percentile values with greater downward pressure as percentiles and percentile values increase. In practical terms, the difference between the contributor percentile values and the PHCS percentiles (the downward bias) increases by an increasingly greater amount at higher percentile levels.

Figure 9
Overall Comparison of Contributor Data Percentiles and PHCS Percentiles
Weighted Average Percent Differences by Percentile
300 CPT Study



306. The weighted average percentile differences at the 80th percentile level for the 2006 comparisons are between 13% and 14.1% at the 80th percentile and 20% to 21% at the 90th. For the 2007 comparisons the differences are between 21.7% and 24.2% for the 80th percentile and 31% and 36% for the 90th. For the 2008 comparisons, the 80th percentile averages are 24% to 26% for the 80th percentiles and 38% to 64% at the 90th. The differences (the downward biases) appear to be increasing not only with percentile but also over time.[100]

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[100] HCPCS values appear to be driving a substantial portion of the difference. This suggests the need to more carefully consider the impact of the HCPCS differences on the overall differences.

2. Medical surgical claims

307. In order to investigate the differences with greater specificity we evaluated both medical surgical and dental claims. Table 20 summarizes the comparisons for medical surgical claims.

Table 20
Summary of Comparisons of Contributor Data Percentiles and PHCS Percentiles
300 CPT Study -Medical Surgical Comparisons

Contributor	Ingenix	Percentile	50	60	70	75	80	85	90	95
2006	2005_2	Avg Diff	6.36	10.24	15.70	19.36	24.73	32.79	45.96	71.20
		Wtd Avg % Diff	5.7%	6.5%	7.5%	8.3%	9.2%	10.8%	13.6%	21.0%
	Claims	708,760,268								
	Comparisons	62,086								
2006	2006_1	Avg Diff	4.53	8.38	13.89	17.47	22.71	30.71	43.85	69.57
		Wtd Avg % Diff	4.0%	4.7%	5.7%	6.3%	7.4%	8.9%	11.8%	19.0%
	Claims	708,760,268								
	Comparisons	62,086								
2007	2006_2	Avg Diff	16.30	21.47	28.87	34.61	42.94	54.03	70.97	102.12
		Wtd Avg % Diff	10.0%	11.2%	12.7%	13.4%	14.8%	16.5%	19.8%	29.8%
	Claims	697,057,469								
	Comparisons	59,769								
2007	2007_1	Avg Diff	14.12	19.29	26.86	32.44	40.63	51.58	67.91	99.31
		Wtd Avg % Diff	9.8%	11.1%	12.8%	13.7%	15.0%	17.0%	20.0%	30.1%
	Claims	738,291,435								
	Comparisons	63,812								
2008	2007_2	Avg Diff	11.79	16.74	23.97	29.32	37.31	48.02	64.42	95.39
		Wtd Avg % Diff	13.0%	15.8%	18.5%	20.4%	23.3%	28.1%	36.2%	55.2%
	Claims	743,523,571								
	Comparisons	63,825								
2008	2008_1	Avg Diff	9.51	14.40	21.43	26.75	34.66	45.48	61.71	92.83
		Wtd Avg % Diff	9.8%	11.0%	13.1%	14.4%	15.6%	17.9%	22.2%	34.1%
	Claims	752,133,236								
	Comparisons	66,219								

308. As with the overall comparison, CPT/geozip combinations without PHCS percentile values and combinations with fewer than 255 claims result in a drop from the 90,000 comparison points to between 60,000 and 66,000 comparisons. Still, the number of claims involved in the comparisons is substantial: between 697 million and 752 million. Once again, all of the differences reported are statistically significant at p= .01

309. The average difference for the comparisons in 2006 range between $22.71 per claim (2006 contributor data compared with May 2006 PHCS version 1) and $24.73 per claim (2006 contributor data compared with November 2006 PHCS version 2) at the 80th percentile. The average

difference at the 90th percentile was $43.85 per claim for the 2006 version 1 PHCS comparison and $45.96 for the PHCS 2005 version 2 comparison at the 90th percentile.

310. The weighted average percent difference between the contributor percentiles and the PHCS percentiles for 2006 were 7.4% for PHCS 2006 version 1 and 9.2% for PHCS 2005 version 2 at the 80th percentile and at the 90th percentile 11.8% for the comparison with PHCS 2006 version 1 and 13.6% for the comparison with PHCS 2005 version 2.

311. Average differences and percent differences were substantially greater for both comparisons using the 2007 data. The weighted average percent differences were 14.8% and 15% at the 80th percentile and 19.8% and 20% for the comparisons at the 90th percentile.

312. The pattern continues with the 2008 comparisons. The weighted average percent differences were 15.6% and 23.3% at the 80th percentiles and 22.2% and 36.2% at the 90th percentile.

313. Like the overall comparisons, the medical surgical comparisons find percentile differences between the contributor data and the PHCS products increasing in percentile level and over time. The medical surgical differences are smaller and more stable than the overall differences. This suggests that the removal of the HCPCS and the dental data from the overall differences reduces percentile values – and that either the HCPCS or the dental differences are greater than the medical surgical differences.

3. Dental claims

314. The specific comparisons also considered dental claims. Table 21 summarizes the comparisons for the dental claims.

Table 21
Summary of Comparisons of Contributor Data Percentiles and PHCS Percentiles
300 CPT Study -Dental Comparisons

Contributor	Ingenix		50	60	70	75	80	85	90	95
2006	**2005_2**	Avg Diff	6.96	10.78	16.13	19.70	24.96	32.83	45.68	70.44
		Wtd Avg % Diff	8.9%	9.5%	10.0%	10.3%	10.7%	11.1%	12.2%	15.9%
	Claims	232,521,870								
	Comparisons	11,558								
2006	**2006_1**		not	available						
2007	**2006_2**		not	available						
2007	**2007_1**	Avg Diff	16.91	18.16	19.29	19.84	20.53	21.56	22.92	25.51
		Wtd Avg % Diff	10.6%	11.2%	11.3%	11.5%	11.8%	11.9%	12.4%	13.7%
	Claims	243,045,337								
	Comparisons	10,661								
2008	**2007_2**	Avg Diff	13.74	14.86	15.96	16.52	17.10	17.93	19.13	21.56
		Wtd Avg % Diff	8.4%	9.0%	9.2%	9.3%	9.6%	9.9%	10.3%	11.6%
	Claims	243,045,337								
	Comparisons	10,661								
2008	**2008_1**	Avg Diff	8.71	9.53	10.41	10.81	11.10	11.78	12.71	14.99
		Wtd Avg % Diff	5.1%	5.5%	5.7%	5.9%	6.2%	6.4%	6.8%	8.0%

Claims	249,027,683
Comparisons	11,065

315. We did not have PHCS, product comparison the data for 2006. So we could not make comparisons for those time frames.[101]

316. The data that were available permitted comparisons of between 10,600 and 11,600 CPT/geozip combinations with 230,000,000 to 249,000,000 claims per comparison. Once again, all of the differences reported are statistically significant at p= .01

317. The comparisons that are available show much less variability from PHCS product version to product version and over time.

318. For example, the weighted average percent difference at the 80th percentile is 10.7% for the comparison of 2006 contributor data with PHCS Version 2 of 2005, 11.8% for the same comparison of 2007 contributor data with version 1 of 2007 PHCS, 9.6% for the same comparison between 2008 contributor data and PHCS 2007 version 2 and 6.2% for the comparison of 2008 contributor data with PHCS 2008 version 1.

319. Similarly, at the 90th percentile the four comparisons (contributor 2006-PHCS 2005 version 2; contributor 2007-PHCS 2007 version 1; contributor 2008-PHCS 2007 version 2; and contributor 2008-PHCS 2008 version 1) produced average weighted percent differences of 12.2%, 12.4%, 10.3% and 6.8%.

320. Further, the average differences for the dental claims were generally less than the average differences overall and for medical surgical claims. This suggests that HCPCS differences are larger than dental and medical surgical differences.[102]

4. Qualitative comparisons

321. In addition to assessing the differences and percent differences. We tracked the number and proportion of combinations where the contributor data percentiles exceeded the PHCS comparisons, the number and proportion of combinations where the contributor data equaled the PHCS values and the number and proportion of combinations where the contributor data percentiles were less than the PHCS values. Table 22 summarizes the results of the qualitative comparisons at the 80th

[101] Continuing efforts are ongoing to obtain this data and to supplement the comparisons with them. Similarly, continuing efforts are underway to obtain earlier years of contributor data for additional comparisons.

[102] Again, suggesting the need for more specific investigation of the HCPCS percentiles in the contributor data.

percentile and Table 24 summarizes the comparisons at the 90th percentile, the two most common percentiles used for UCR adjudication that represent more than 65% of the adjudications.

322. The 80th percentile comparisons contained in Table 22 are based on a substantial number of CPT/geozip combination comparisons. As a result, the qualitative differences are statistically significant at p=.01.

Table 22
Qualitative Comparisons of Contributor Data Percentiles and PHCS Percentiles
Contributor Percentiles Greater Than, Equal to and Less Than PHCS Comparisons
At the 80th Percentile
300 CPT Study

			Greater	Equal	Less	Greater	Equal	Less
2006	**2005_1**	**Overall**	52,874	14,996	8,141	69.6%	19.7%	10.7%
		Med/Surg	40,961	14,527	7,789	64.7%	23.0%	12.3%
		Dental	11,772	382	314	94.4%	3.1%	2.5%
2006	**2006_1**	**Overall**	39,498	20,419	8,352	57.9%	29.9%	12.2%
		Med/Surg	38,707	20,136	8,145	57.8%	30.1%	12.2%
2007	**2006_2**	**Overall**	44,210	10,167	8,818	70.0%	16.1%	14.0%
		Med/Surg	41,442	9,857	8,470	69.3%	16.5%	14.2%
2007	**2007_1**	**Overall**	55,276	13,425	9,415	70.8%	17.2%	12.1%
		Med/Surg	42,018	12,855	8,939	65.8%	20.1%	14.0%
		Dental	10,397	149	115	97.5%	1.4%	1.1%
2008	**2007_2**	**Overall**	52,759	16,532	9,103	67.3%	21.1%	11.6%
		Med/Surg	39,254	15,881	8,690	61.5%	24.9%	13.6%
		Dental	10,329	209	123	96.9%	2.0%	1.2%
2008	**2008_1**	**Overall**	50,718	21,491	9,228	62.3%	26.4%	11.3%
		Med/Surg	37,224	20,263	8,731	56.2%	30.6%	13.2%
		Dental	10,250	600	215	92.6%	5.4%	1.9%

323. The dental claims illustrate with the greatest clarity the effect of the PHCS downward bias. Overall, the contributor data comparison with the PHCS product percentiles shows contributor percentiles greater than PHCS percentiles 95% of the time and less than the PHCS percentiles only two percent of the time. Clearly, there is an "across the board" downward bias in the PHCS dental percentiles.

324. While not as pronounced, the same bias can be seen in the qualitative comparison of the medical surgical percentiles. The six comparisons of the contributor percentiles with corresponding

PHCS percentiles find the contributor percentiles greater 65%, 58%, 69%, 66%, 62% and 56% of the time. Contributor percentiles are less than corresponding PHCS percentiles 12%, 14%, 14%, 14%, 13%, and 13% of the time.

325. Overall, contributor data percentiles were greater than corresponding PHCS percentiles 70%, 58%, 70%, 71%, 67% and 62% of the time while they were less 11%, 12% 14%, 12%, 12% and 11% of the time.

326. Contributor data percentiles for the 80th percentile are greater than corresponding PHCS percentiles in a ratio of six or seven to one. This is consistent with systematic downward bias.

327. In order to evaluate whether the qualitative comparison results are "random" or nonrandom we also conducted a correlation analysis of the relationship between numbers of contributor data claims in the CPT/geozip combination, the median value of the billed charge for the contributor data and whether the contributor 80th percentile was greater than, equal to or less than the corresponding PHCS 80th percentile for the same CPT/geozip combination. We used the 78,148 CPT/geozip combinations from the of 300 CPT Study for the 2008 contributor data comparison with the 2008 version 1 of the PHCS. The hypothesis for the study was that the incidence of greater percentile values and less percentile values for the contributor data are random by nature (not the result of specific Ingenix processes).

328. Table 23 shows the Pearson correlation coefficients for the correlation analysis. All results are statistically significant at p=.01.

Table 23
Correlation Coefficients (Pearson) for 80th Percentile Comparisons
Contributor Percentile Values Greater Than, Equal To or Less Than
Corresponding PHCS Percentile Values
2008 Contributor Data, 2008 Version 1 PHCS

	Contributor Claims	Median Charge	GREATER	EQUAL	LESS
Contributor Claims	1.000	-.076**	.021**	-.012**	-.014**
Median Charge	-.076**	1.000	.081**	-.060**	-.039**
GREATER	.021**	.081**	1.000	-.766**	-.456**
EQUAL	-.012**	-.060**	-.766**	1.000	-.223**
LESS	-.014**	-.039**	-.456**	-.223**	1.000

** Indicate statistical significance at p=.01

329. The likelihood that the contributor data percentiles are greater than the PHCS percentiles increases with the number of contributor claims and the median charge. Greater numbers of claims and greater dollar value of claims increases the likelihood that the contributor data percentiles

will be greater. Conversely, fewer claims increase the likelihood that the PHCS values will be greater. The small likelihood that a PHCS percentile level will be greater than a contributor data percentile level is not random at all, but is inversely related to the number of claims and the level of charges.[103] This requires us to reject the null hypothesis that the incidence of the differences is random and to accept the alternative hypothesis that there is a pattern when the contributor data percentiles are greater and when they are less. Not only is there a downward bias, but the bias is related to the "importance" of the billed charges in terms of numbers of claims and their level. PHCS percentiles are more likely to be biased downward for more numerous higher value claims.

330. Defendants' experts have conducted several comparative analyses of the Ingenix products and point to the fact that "some" comparative percentiles are less than the PHCS percentiles (with some greater and some equal to) create lack of common impact as the basis for denial of class certification. However, such argument misses the point. The question is not whether some of the values are greater, and some are less, but rather the proportions of the comparisons that are greater compared to the proportions of the comparisons that are less and the reason why some of the PHCS values are less. It appears that the minimal number of values that are less have occurred based on a reason related to the Ingenix processing.

331. If the contributor percentiles were essentially the same as the PHCS percentiles we would expect to see the comparisons follow a bell curve with most of the comparisons equal and the same proportion of comparative values higher than and lower than the other. In other words, the percent greater should equal the percent less. This is clearly not the case for the comparison of the contributor data to the PHCS products.

332. We also conducted the qualitative comparison for the 90th percentile. Table 24 summarizes the results.

Table 24
Qualitative Comparisons of Contributor Data Percentiles and PHCS Percentiles
Contributor Percentiles Greater Than, Equal to and Less Than PHCS Comparisons
At the 90th Percentile
300 CPT Study

			Greater	Equal	Less	Greater	Equal	Less
2006	**2005_1**	**Overall**	55,489	13,300	7,222	73.0%	17.5%	9.5%

[103] And, as noted, there is almost nonexistent likelihood that a PHCS percentile value for a dental claim will be greater than the corresponding contributor data percentile.

		Med/Surg	63,277	43,611	12,861	68.9%	20.3%	10.8%
		Dental	11,728	362	378	94.1%	2.9%	3.0%
2006	**2006_1**	**Overall**	68,269	42,972	18,066	62.9%	26.5%	10.6%
		Med/Surg	66,988	42,119	17,831	62.9%	26.6%	10.5%
2007	**2006_2**	**Overall**	63,195	46,447	8,836	73.5%	14.0%	12.5%
		Med/Surg	59,769	43,533	8,614	72.8%	14.4%	12.8%
2007	**2007_1**	**Overall**	57,847	11,895	8,354	74.1%	15.2%	10.7%
		Med/Surg	44,487	11,419	7,906	69.7%	17.9%	12.4%
		Dental	10,339	168	154	97.0%	1.6%	1.4%
2008	**2007_2**	**Overall**	55,563	14,737	8,094	70.9%	18.8%	10.3%
		Med/Surg	42,004	14,157	7,664	65.8%	22.2%	12.0%
		Dental	10,233	256	172	96.0%	2.4%	1.6%
2008	**2008_1**	**Overall**	53,887	19,530	8,020	66.2%	24.0%	9.8%
		Med/Surg	40,376	18,358	7,484	61.0%	27.7%	11.3%
		Dental	10,089	706	270	91.2%	6.4%	2.4%

333. At the 90th percentile the contributor dental percentile values are still greater than the PHCS percentiles 95% of the time and less only two percent of the time although the differences are slightly less than at the 80th percentile.

334. For the overall values and for the medical surgical percentiles the percent greater increased by three percent overall and four percent for medical surgical claims and the percentage of contributor percentiles that were less than PHCS correlates dropped by approximately 1.5% both for the overall and for the medical surgical comparisons.

335. The 90th percentile qualitative comparisons mirror the 80th percentile comparisons with even more pronounced results.

336. Accordingly, the quantitative and qualitative results of the 300 CPT study require rejection of the null hypothesis of lack of downward bias in the PHCS percentiles and acceptance of the alternative hypothesis that the PHCS percentiles are biased downward. The findings are statistically significant at p=.01 and are marked.

B. The 350 CPT study

337. As noted above, in order to confirm and extend the results from the 300 CPT study we independently compared CPT/geozip percentile values for the 350 CPT codes with the most claims and the 450 geozips with the most claims in the contributor data.[104] The analysis was limited to medical

[104] The 350 most commonly used CPT codes and the 450 most commonly used geozips were identified using 2007 and 2008 contributor data. The 2008 comparison extended the evaluation to all geozips in the data to broaden the analysis even more.

and surgical claims – about half of the 1.4 billion annual contributor claims. The 157,500 CPT/geozip combinations represented 80% of the contributor medical surgical data.

338. Like the 300 CPT Study, data were cleaned to eliminate invalid CPT codes and invalid geozips, to eliminate negative and zero billed charges and to eliminate modifiers as a source of bias. As noted above, approximately 16% of the contributor medical surgical data has billed charges with modifiers. Elimination of modifiers dropped the total annual number of claims in the data to approximately 600 million claims lines. Percentile values were generated for the 50th, 60th, 70th, 75th, 80th, 85th, 90th and 95th percentiles.

339. As with the 300 CPT Study, comparisons were eliminated where we did not have PHCS product values for comparisons and where the total claims for the comparison were less than 255.[105]

340. Contributor data for 2006-2008 were evaluated. Monthly files for 2006 and 2008 and the ten piecemeal files for 2007. Since 2006 and 2008 had monthly files the study analyzed contributor data for the first half of 2006, the second half of 2006, all of 2007 (since it could not be halved), the first half of 2008 and the second half of 2008.

341. The contributor results were paired with the most likely contemporaneous PHCS product: 2005 version 2 for the contributor 2006 first half; 2006 version 1 for the contributor 2006 second half, 2006 version 2 and 2007 version 1 for the 2007 contributor data, 2007 version 2 for the first half of 2008 and 2008 version 1 for the second half of 2008.

1. Quantitative results

342. Table 25 summarizes the quantitative results derived from comparing percentile values for the 157,500 CPT/ geozip combinations.

Table 25
Summary of Quantitative Results of 350 CPT Study

Contrib	Ingenix	2006_1	50	60	70	75	80	85	90	95
2006_1	2005_2	Avg diff	40.15	45.28	52.40	57.35	64.06	74.00	89.22	118.62
		Wtd avg % diff	13.1%	14.7%	17.1%	18.2%	19.9%	22.5%	26.3%	40.1%

[105] As noted in the previous section, since differences are likely to be greater with smaller claim values, inclusion of smaller claim comparisons may well increase the differences.

	Claims	476,415,996								
	Combinations	67,412								
2006_1	2006_1	Avg	37.53	42.35	49.40	54.26	60.90	70.45	85.18	113.91
		Wtd avg	10.4%	11.5%	13.7%	14.9%	16.6%	18.8%	22.3%	35.7%
	Claims	432,257,116								
	Combinations	68,516								
2007__	2006_2	Avg	31.00	36.24	42.34	46.39	52.01	60.82	75.58	110.01
		Wtd avg	9.9%	10.6%	11.4%	11.9%	12.7%	13.6%	15.6%	20.4%
	Claims	463,309,377								
	Combinations	46,404								
2007__	2007_1	Avg	28.80	33.82	39.62	43.44	48.84	57.40	71.60	104.83
		Wtd avg	8.2%	8.7%	9.5%	9.9%	10.8%	11.8%	13.5%	18.0%
	Claims	463,309,377								
	Combinations	51,106								
2008_1	2007_2	Avg	49.58	60.16	76.04	87.90	102.94	123.32	154.29	208.60
		Wtd avg	21.7%	24.7%	27.0%	29.5%	33.2%	38.2%	46.4%	69.0%
	Claims	647,913,518								
	Combinations	103,030								
2008_2	2007_1	Avg	44.95	53.95	67.07	77.38	90.38	107.75	134.20	181.66
		Wtd avg	22.0%	25.1%	29.3%	32.1%	35.7%	40.8%	49.5%	96.6%
	Claims	676,379,074								
	Combinations	108,061								

343. A substantial portion of these comparisons were not able to be used because there were no values in the PHCS product for comparison (40,000 to 50,000) and a substantial number had less than 255 claims (another 40,000 to 50,000).

344. Indeed, analysis of the 4,294,950 MDR medical surgical CPT/geozip combinations for the second release of 2008 shows the following:

a. Total combinations: 4,294,950

b. Combinations with zeros for percentile values: 2,827,013

c. Combinations with nine or fewer claims: 2,132,794

d. Combinations with nine to 254 claims: 694,219

e. Combinations with enough claims to permit comparisons: 190,126

345. Since the PHCS is constructed with the same data as MDR, only about 190,000 combinations will have enough data for comparisons.

346. The number of available comparisons in the 350 CPT study ranged from 46,400 for 2007 contributor data to 108,000 for the 2008 contributor data. The comparisons involved a substantial number of claim lines: 432 million for the second half of 2006 to 676 million for the second half of 2008.

The number of combinations available for comparison and the millions of claims (limiting reported comparisons to 255 claims or more) means that all results are statistically significant at p=.01.

347. Overall, the results are consistent with fully supportive of the 300 CPT study: contributor percentile values are consistently higher than corresponding PHCS percentile values requiring rejection of the hypothesis that there is no downward bias in the PHCS percentiles and acceptance of the null hypothesis of downward bias.

348. The weighted average percent difference for the 80th percentile values for the contributor data compared with the PHCS percentile values are (all significant at p=.01).

a. 19.9% higher for the first half of 2006 compared with PHCS 2005 version 2,

b., 16.6% higher for the second half of 2006 compared with the 2006 version 1 PHCS,

c. 12.7% higher for 2007 data compared with 2006 version 2 PHCS,

d. 10.8% higher for 2007 data compared with 2007 version 1 PHCS,

e. 32.2% higher for 2008 first half compared with 2007 version 2 PHCS,

f. 35.7% higher for 2008 second half compared with 2008 version 1 PHCS.

349. The 2008 analysis expanded the number of geozips in the study. The expansion incorporated a greater number of smaller claims comparisons than the 2007 and the 2006 comparisons. As a result, the weighted average percent difference rose (as hypothesized from several of the results in the 300 CPT Study).

350. The geometric expansion of percent differences by percentile level is consistent with the 300 CPT Study, as are the higher average differences and average percent differences for the 90th percentile.

a. 26.3% higher for the first half of 2006 compared with PHCS 2005 version 2,

b. 22.3% higher for the second half of 2006 compared with the 2006 version 1 PHCS,

c. 15.6% higher for 2007 data compared with 2006 version 2 PHCS,

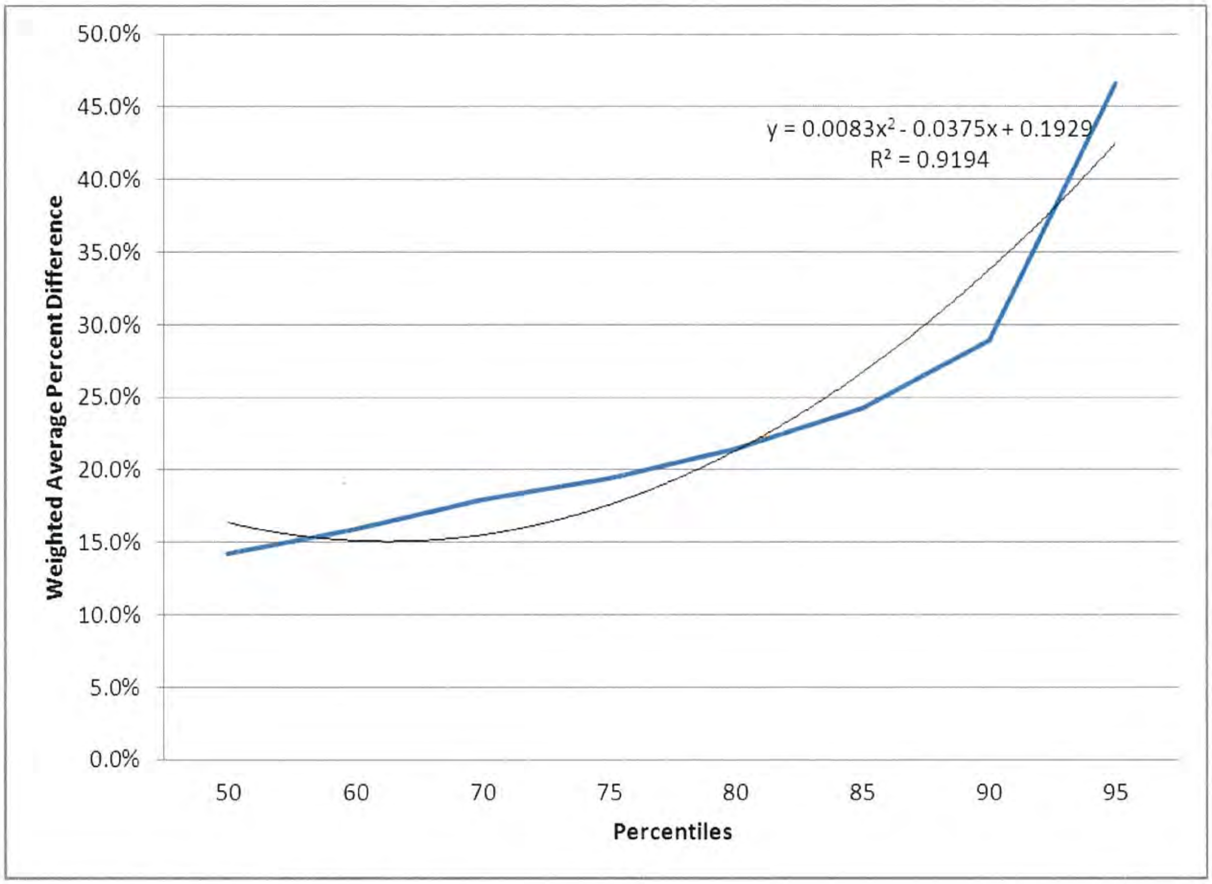
d. 13.5% higher for 2007 data compared with 2007 version 1 PHCS,

e. 46.4% higher for 2008 first half compared with 2007 version 2 PHCS,

f. 49.5% higher for 2008 second half compared with 2008 version 1 PHCS

351. As shown in Figure 10, the geometric expansion by percentile level for the 350 CPT study is markedly similar to the 300 CPT Study results.

Figure 10
Overall Comparison of Contributor Data Percentiles and PHCS Percentiles
Weighted Average Percent Differences by Percentile
350 CPT Study



2. Qualitative Results

352. The qualitative results for the 350 CPT study also mirror and confirm the qualitative results of the 300 CPT study. Table 26 sets forth the qualitative results for the 350 CPT Study at the 80th percentile.

Table 26
Qualitative Results for 350 CPT Study

Contrib	Ingenix	Greater	Equal	Less	Greater	Equal	Less
2006_1	2005_2	38,242	18,843	11,430	55.8%	27.5%	16.7%
2006_1	2006_1	41,382	15,514	11,568	60.4%	22.7%	16.9%
2007__	2006_2	27,399	11,720	7,285	59.0%	25.3%	15.7%
2007__	2007_1	29,029	10,674	6,701	62.6%	23.0%	14.4%
2008_1	2007_2	67,083	17,605	18,342	65.1%	17.1%	17.8%
2008_2	2008_1	66,236	22,371	19,454	61.3%	20.7%	18.0%

353. The qualitative results show that the contributor medical surgical data provides 80th percentile values greater than PHCS comparable values 59% to 65% of the time and that the contributor

data percentiles are less than the PHCS values 14% to 18% of the time. These results are nearly identical with those in the 300 CPT study.

354. As a result, like the 300 CPT study, the qualitative study results for the 350 CPT Study require rejection of the hypothesis that there is no downward bias in the Ingenix PHCS percentiles and acceptance of the alternative hypothesis that there is downward bias.

C. Verification of the 300 CPT Study and the 350 CPT Study

355. As additional verification of the findings of the 300 CPT study and the 350 CPT study we compared percentile values for the CPT/geozip combinations that permitted such comparison. Comparisons were available for 34,225 combinations representing 607 million claims. The reasons why only one third of the 300 CPT Study and one fifth of the 350 CPT Study combinations were available for comparison relate to differences in design. The 300 CPT study included HCPCS and dental codes, used fewer geozip and selected geozip at random. Also, comparisons were not made where there were fewer than 255 claims for the combination, substantially limiting the number of combinations that could be compared. Nevertheless, 34,000 combinations with 600 million claims provides the basis for a substantial comparison.

356. Table 27 outlines the result of the comparisons.

Table 27
Comparison and Verification of the 300 CPT Study and the 350 CPT Study

Percentile	50	60	70	75	80	85	90	95
Avg diff	(4.94)	(4.47)	(4.25)	(4.01)	(4.12)	(4.12)	(4.67)	(5.64)
Avg % diff	-0.3%	-0.5%	-0.3%	-0.2%	0.1%	0.2%	0.8%	1.8%

357. The 300 CPT Study produced percentile values that were $4.01 to $5.64 lower than the same percentiles for the 350 CPT Study.[106] The average percent differences were lower for the 300 CPT Study in the lower percentile ranges but higher for the upper CPT ranges. Overall there was virtually no difference between the percentile values for the two studies (less than 1% for all but the 95th percentile), particularly for the 80th percentile where the difference was 0.1%.

358. The comparison provides far different results than the comparisons of the contributor data and the PHCS product. Study results for the 300 CPT study and the 350 CPT Study do not show systematic bias relative to each other. The Study results are consistent and verify one another.

[106] These differences are significant at p=.01. The relative size of the difference is very small as shown by the average percent differences.

D. Comparison of percentile values in MDR and PHCS

359. For an additional investigation of the bias or lack of bias in the PHCS percentiles there is another standard that is available that uses the same data as PHCS – the MDR product. As described above, Ingenix offers two percentile data products, MDR and PHCS, which both provide billed charge percentiles by CPT and geozip. Since both of these products are built from the same data[107] in theory, they should provide the same percentile values. However, the way that the two products construct percentile values from the same data is different

360. All of the MDR percentiles are derived by grouping CPTs, normalizing them by dividing by a relative value, arranging the normalized values into percentiles end by multiplying the relative values to derived percentile values by CPT.

361. PHCS percentiles are directly developed by CPT and geozip although some of them are derived but using a different relative value system.

362. The MDR products are updated four times per year and include a consumer price index inflation factor. The PHCS products are updated twice per year and do not include an inflation factor.

363. In order to test the hypothesis that there is no difference between the MDR and PHCS percentiles we compared the Ingenix product values for the 196 most common CPT/geozip combinations at the 75th, 80th and 85th percentiles.[108] We used the second cycle of 2008 for the MDR for comparison with the first PHCS release for 2008.

364. We started by constructing percentile values for MDR – multiplying the MDR value for the CPT/geozip combinations by the applicable MDR relative value. We compared these values with the PHCS values for the equivalent CPT/geozip. Table 28 summarizes the results.

Table 28
Comparison of Percentile Values for MDR and PHCS
MDR Release 2 of 2008 and PHCS Version 1 for 2008

geozip	cpt	mdr count	mdr_75	mdr_80	mdr_85	phcs count	p75	p80	p85	PctD75	PctD80	PctD85

[107] Gee Depo. at 124:17-125:18.

[108] We attempted a comparison for 200 but five combinations could not be compared.

272	80050	999,999	193.60	196.35	200.20	1,120,171	190	193	197	1.89%	1.74%	1.62%
272	80053	999,999	52.36	54.32	56.56	1,654,965	51	54	55	2.67%	0.59%	2.84%
272	80061	999,999	94.08	96.96	104.96	2,378,848	91	92	94	3.38%	5.39%	11.66%
272	85025	999,999	42.55	43.66	44.96	1,509,589	42	43	44	1.31%	1.53%	2.17%
117	99213	999,999	107.30	122.13	127.31	1,569,996	100	115	125	7.30%	6.20%	1.84%
770	99213	999,999	98.67	102.12	109.37	1,109,408	97	100	108	1.72%	2.12%	1.26%
752	99213	982,941	110.40	116.27	118.34	982,941	109	115	117	1.28%	1.10%	1.14%
750	99213	902,562	105.57	107.30	111.09	902,562	104	105	110	1.51%	2.19%	0.99%
117	97110	863,982	60.63	61.34	66.27	863,982	60	60	65	1.05%	2.23%	1.95%
272	84443	847,527	107.94	110.04	112.14	847,526	106	108	110	1.83%	1.89%	1.95%
100	99213	845,472	157.67	176.99	178.71	845,472	155	175	175	1.72%	1.13%	2.12%
70	99213	826,341	101.78	102.12	112.13	826,341	100	100	110	1.78%	2.12%	1.93%
21	99213	819,097	153.18	172.16	172.50	819,097	150	169	169	2.12%	1.87%	2.07%
193	80061	803,645	108.16	111.36	112.32	803,645	110	111	114	-1.67%	0.32%	-1.47%
80	99213	796,105	96.95	101.78	106.26	796,105	95	100	105	2.05%	1.78%	1.20%
272	88175	784,330	117.20	117.39	117.39	784,330	115	115	115	1.91%	2.08%	2.08%
100	97110	779,484	86.72	98.47	99.88	779,484	80	80	85	8.39%	23.08%	17.50%
272	83036	719,689	75.06	75.60	77.76	719,689	74	74	77	1.43%	2.16%	0.99%
631	99213	654,166	96.26	100.05	102.12	654,166	95	98	100	1.32%	2.09%	2.12%
115	99213	649,638	122.13	127.31	127.65	649,638	105	120	125	16.31%	6.09%	2.12%
606	80061	646,418	95.68	104.32	111.68	646,403	104	115	115	-8.00%	-9.29%	-2.89%
303	99213	631,636	102.12	106.26	111.09	631,636	100	105	110	2.12%	1.20%	0.99%
770	99214	619,975	151.50	153.00	163.50	619,975	150	150	161	1.00%	2.00%	1.55%
852	97110	606,920	55.46	59.46	61.34	606,920	49	50	50	13.18%	18.91%	22.67%
300	99213	596,716	95.91	100.74	104.19	596,716	95	100	103	0.96%	0.74%	1.16%
117	99214	595,375	152.50	153.00	167.00	595,375	150	150	165	1.67%	2.00%	1.21%
272	88142	590,954	100.13	100.13	100.13	590,954	98	98	98	2.17%	2.17%	2.17%
272	87086	588,265	78.30	78.30	81.30	588,265	64	64	67	22.34%	22.34%	21.34%
88	99213	583,822	96.95	101.78	110.75	583,822	95	100	110	2.05%	1.78%	0.68%
70	97110	581,634	66.27	71.44	76.38	581,634	65	70	75	1.95%	2.06%	1.83%
193	80053	573,187	50.12	50.40	50.40	573,187	50	50	50	0.24%	0.80%	0.80%
70	99214	570,019	151.50	153.00	163.00	570,019	150	150	160	1.00%	2.00%	1.88%
752	99214	560,083	174.00	183.00	184.50	560,083	171	181	182	1.75%	1.10%	1.37%
272	84153	543,672	116.48	122.72	128.44	543,672	115	122	127	1.29%	0.59%	1.13%
303	97110	534,793	55.46	56.17	60.63	534,793	55	55	60	0.84%	2.12%	1.05%
100	90806	533,258	178.88	183.60	203.85	533,258	175	180	200	2.21%	2.00%	1.93%
100	99214	527,868	224.50	235.00	254.50	527,868	220	230	250	2.05%	2.17%	1.80%
750	97110	521,418	59.93	65.80	66.74	521,418	55	55	55	8.95%	19.64%	21.35%
441	99213	518,877	101.43	128.00	132.83	518,877	99	127	131	2.45%	0.78%	1.39%
301	99213	517,537	91.77	97.64	102.12	517,537	90	96	101	1.97%	1.70%	1.11%
247	99213	493,267	90.74	94.88	96.95	493,267	89	93	95	1.95%	2.02%	2.05%
105	99213	492,098	127.31	131.45	147.66	492,098	120	125	135	6.09%	5.16%	9.38%
606	85025	492,093	36.26	40.89	49.40	492,085	36	40	48	0.72%	2.21%	2.91%
606	80053	489,785	55.72	67.48	68.32	489,774	55	67	68	1.31%	0.72%	0.47%
750	99214	489,125	162.00	164.00	172.00	489,125	160	161	170	1.25%	1.86%	1.18%
142	99213	482,005	76.59	80.73	85.91	482,005	75	80	85	2.12%	0.91%	1.06%
452	99213	480,018	81.77	86.94	91.77	480,018	81	85	90	0.94%	2.28%	1.97%
100	97140	479,702	81.54	86.58	91.08	479,702	80	85	90	1.93%	1.86%	1.20%
272	88305	476,159	77.42	78.40	78.40	447,751	186	186	186	-58.38%	-57.85%	-57.85%
606	36415	474,309	16.15	18.38	20.25	474,309	16	18	20	0.92%	2.09%	1.26%
21	99214	472,370	268.00	268.00	268.50	472,370	263	263	263	1.90%	1.90%	2.09%
852	99213	472,024	91.77	96.60	101.78	472,024	90	95	100	1.97%	1.68%	1.78%
606	99213	462,450	117.65	120.41	125.93	462,450	116	119	124	1.42%	1.18%	1.55%
889	99213	461,378	112.13	118.34	126.27	461,378	110	116	125	1.93%	2.01%	1.02%
600	97110	459,281	66.27	66.51	69.33	459,281	65	65	68	1.95%	2.32%	1.95%
272	86003	457,163	36.85	37.73	38.17	457,163	36	37	38	2.36%	1.97%	0.45%
117	97140	455,822	61.20	66.24	70.74	455,822	60	65	70	2.00%	1.91%	1.06%
193	85025	455,327	34.78	34.97	35.52	455,327	34	34	35	2.29%	2.84%	1.49%
760	99213	454,125	100.74	101.09	103.16	454,125	99	100	102	1.76%	1.08%	1.13%
850	99213	450,600	91.08	95.57	99.02	450,600	90	94	97	1.20%	1.66%	2.08%
191	99213	448,799	104.88	119.37	126.27	448,799	104	118	125	0.85%	1.16%	1.02%
111	99213	441,362	112.13	127.65	151.80	441,362	125	133	150	-10.30%	-4.02%	1.20%
152	83914	439,558	6.20	6.20	6.20	439,558	13	16	25	-52.31%	-61.25%	-75.20%
272	81003	439,039	110.40	112.50	115.20	439,039	35	36	37	215.43%	212.50%	211.35%
432	99213	437,769	88.67	91.77	92.12	437,769	87	90	90	1.91%	1.97%	2.35%

770	97110	437,494	66.51	69.33	73.09	437,494	59	60	70	12.72%	15.54%	4.41%
18	99213	437,173	107.30	116.96	122.48	437,173	105	115	120	2.19%	1.70%	2.06%
606	97110	434,471	75.44	78.96	80.84	434,471	68	70	73	10.93%	12.80%	10.74%
532	99213	426,907	117.30	120.41	127.65	426,907	115	119	125	2.00%	1.18%	2.12%
430	99213	422,867	81.77	83.84	87.98	422,867	80	82	87	2.21%	2.24%	1.12%
272	84436	420,485	61.20	61.92	65.52	420,484	47	48	48	30.21%	29.00%	36.50%
554	99213	419,708	121.10	122.48	123.51	419,708	119	121	121	1.76%	1.22%	2.07%
282	99213	416,553	116.27	121.44	138.00	416,553	114	120	137	1.99%	1.20%	0.73%
113	99213	415,061	127.31	135.93	151.80	415,061	120	125	125	6.09%	8.74%	21.44%
77	99213	401,591	101.09	102.12	107.30	401,591	100	100	105	1.08%	2.12%	2.19%
272	87621	393,101	205.60	208.00	208.80	393,101	204	204	204	0.78%	1.96%	2.35%
201	99213	392,964	101.78	106.26	116.96	392,964	100	105	115	1.78%	1.20%	1.70%
782	99213	391,491	91.77	96.60	101.09	391,491	90	95	99	1.97%	1.68%	2.11%
432	95004	389,937	5.83	6.58	6.63	389,937	6	7	7	-2.92%	-6.07%	-5.36%
600	99213	384,402	110.40	114.54	120.75	384,402	108	112	118	2.22%	2.27%	2.33%
193	80050	383,730	190.30	191.95	192.50	383,730	188	188	191	1.22%	2.10%	0.79%
212	99213	374,868	102.81	107.30	111.09	374,868	101	105	110	1.79%	2.19%	0.99%
850	97110	374,737	52.88	58.75	61.34	374,737	45	48	50	17.50%	22.40%	22.67%
334	99213	374,250	101.78	103.85	108.33	374,250	100	102	107	1.78%	1.81%	1.24%
272	81001	371,340	117.76	120.00	122.88	371,338	38	39	40	209.89%	207.69%	207.20%
80	99214	370,944	137.50	146.50	149.50	370,944	135	145	147	1.85%	1.03%	1.70%
109	99213	369,467	125.93	127.65	151.11	369,467	115	125	125	9.50%	2.12%	20.89%
761	99213	368,118	101.78	107.30	116.96	368,118	100	105	115	1.78%	2.19%	1.70%
115	97110	364,396	73.09	76.38	79.67	364,396	65	65	75	12.44%	17.50%	6.22%
303	99214	364,157	156.00	166.00	172.00	364,157	155	163	170	0.65%	1.84%	1.18%
80	97110	363,615	66.27	70.74	74.26	363,615	65	70	73	1.95%	1.05%	1.73%
190	99213	357,997	91.08	91.77	96.95	357,997	90	90	95	1.20%	1.97%	2.05%
752	36415	353,390	18.38	18.38	20.22	353,390	18	18	20	2.09%	2.09%	1.10%
852	99214	349,323	142.50	149.50	158.00	349,323	140	148	155	1.79%	1.01%	1.94%
775	99213	348,782	86.94	94.88	98.67	348,782	85	93	97	2.28%	2.02%	1.72%
980	99213	346,097	106.26	110.06	120.41	346,097	104	108	120	2.17%	1.90%	0.34%
272	84439	344,384	102.00	103.20	109.20	344,384	120	122	125	-15.00%	-15.41%	-12.64%
945	99213	342,584	102.12	107.30	117.99	342,584	100	106	116	2.12%	1.22%	1.72%
981	99213	342,440	129.38	130.41	131.79	342,440	127	129	129	1.87%	1.09%	2.16%
117	36415	337,594	18.37	20.22	20.36	337,594	18	20	20	2.07%	1.10%	1.82%
500	99213	336,577	86.25	89.01	97.29	336,577	85	88	96	1.47%	1.15%	1.34%
328	99213	334,653	104.88	107.30	115.23	334,653	103	105	113	1.83%	2.19%	1.97%
150	99213	331,787	79.35	80.73	81.77	331,787	78	80	80	1.73%	0.91%	2.21%
76	99213	330,476	102.81	115.23	121.44	330,476	101	113	120	1.79%	1.97%	1.20%
193	88142	329,429	72.42	73.27	81.77	329,429	72	72	81	0.58%	1.76%	0.95%
752	88305	329,004	340.06	345.94	409.64	263,370	250	250	335	36.02%	38.38%	22.28%
88	99214	327,901	151.00	153.00	158.00	327,901	150	150	155	0.67%	2.00%	1.94%
922	99070	327,605	0.03	0.03	0.04	304,795	3	4	4	-98.88%	-99.15%	-99.08%
110	99213	325,626	117.30	126.27	127.31	325,626	110	125	150	6.64%	1.02%	-15.13%
770	95004	324,203	8.15	8.18	8.18	324,203	8	8	8	1.88%	2.19%	2.19%
327	99213	323,776	101.78	103.85	104.19	323,776	100	102	103	1.78%	1.81%	1.16%
731	99213	323,729	91.77	92.81	96.95	323,729	90	91	96	1.97%	1.98%	0.98%
170	99213	321,573	77.97	81.42	88.67	321,573	77	80	87	1.26%	1.78%	1.91%
630	99213	321,245	85.91	87.98	91.77	321,245	84	87	90	2.27%	1.12%	1.97%
70	97140	320,300	66.42	71.28	75.78	320,300	65	70	75	2.18%	1.83%	1.04%
272	85652	317,937	46.50	50.00	56.38	317,937	41	41	42	13.41%	21.95%	34.23%
100	36415	317,359	26.60	30.33	30.54	317,359	30	30	30	-11.32%	1.09%	1.81%
140	99213	316,597	70.73	72.45	75.90	316,597	70	71	75	1.04%	2.04%	1.20%
74	99213	315,366	101.78	102.12	115.92	315,366	100	100	114	1.78%	2.12%	1.68%
71	99213	313,435	112.13	127.31	143.52	313,435	110	125	141	1.93%	1.84%	1.79%
773	99213	311,594	91.08	93.84	102.12	311,594	90	92	100	1.20%	2.00%	2.12%
100	95004	311,539	11.98	12.23	12.25	311,539	12	12	12	-0.21%	1.88%	2.08%
889	99214	309,263	163.50	171.50	183.50	309,263	160	169	180	2.19%	1.48%	1.94%
105	97110	308,030	75.44	77.55	91.89	308,030	70	75	75	7.76%	3.40%	22.51%
152	99213	307,293	85.56	86.94	92.81	307,293	84	85	91	1.86%	2.28%	1.98%
925	99070	306,166	0.03	0.03	0.04	269,008	3	3	4	-98.87%	-98.87%	-98.95%
631	99214	305,673	145.00	153.00	157.00	305,673	142	150	154	2.11%	2.00%	1.95%
272	80076	303,308	73.50	75.75	82.00	303,308	49	49	52	50.00%	54.59%	57.69%
802	99213	300,061	93.84	99.71	104.88	300,061	92	98	104	2.00%	1.74%	0.85%
300	99214	298,654	146.00	151.00	153.00	298,654	144	150	150	1.39%	0.67%	2.00%

68	99213	298,212	103.16	111.09	116.27	298,212	102	110	115	1.13%	0.99%	1.10%
606	84443	297,468	110.46	110.46	112.14	297,464	108	108	110	2.28%	2.28%	1.95%
787	99213	296,715	98.67	99.02	106.26	296,715	97	97	105	1.72%	2.08%	1.20%
750	95165	295,578	0.09	0.09	0.09	293,064	18	19	20	-99.51%	-99.54%	-99.56%
191	80061	293,923	110.40	111.68	114.24	293,923	112	114	114	-1.43%	-2.04%	0.21%
272	85610	292,503	48.36	52.00	58.63	292,503	48	51	58	0.75%	1.96%	1.09%
193	84443	290,256	123.48	133.56	147.00	290,256	110	110	111	12.25%	21.42%	32.43%
452	99214	289,988	128.00	136.50	143.50	289,988	125	135	140	2.40%	1.11%	2.50%
193	99213	288,939	81.77	86.60	89.70	288,939	80	85	88	2.21%	1.88%	1.93%
180	99213	288,931	76.59	76.59	80.73	288,931	75	75	80	2.12%	2.12%	0.91%
606	88142	288,048	71.74	78.20	86.70	288,047	70	77	86	2.49%	1.56%	0.81%
703	99213	287,884	84.53	86.94	93.50	287,884	83	85	93	1.84%	2.28%	0.53%
193	97110	287,413	47.00	51.00	51.47	287,413	46	50	51	2.17%	1.99%	0.91%
272	80048	287,145	73.44	78.72	82.80	287,143	48	50	52	53.00%	57.44%	59.23%
752	85025	287,046	37.56	37.74	38.85	287,037	37	37	38	1.50%	2.00%	2.24%
100	97112	286,917	75.44	76.36	76.59	286,917	75	75	75	0.59%	1.81%	2.12%
300	97110	286,889	51.00	51.00	55.93	286,889	50	50	55	1.99%	1.99%	1.69%
605	97110	286,814	71.44	76.38	77.32	286,814	63	68	68	13.40%	12.32%	13.70%
441	99214	286,341	154.00	191.50	193.00	286,341	152	189	189	1.32%	1.32%	2.12%
272	87491	286,332	132.80	133.60	135.20	286,331	130	133	133	2.15%	0.45%	1.65%
601	99213	285,777	104.54	107.64	115.92	285,777	102	105	114	2.49%	2.51%	1.68%
980	97110	285,685	55.23	56.64	59.93	285,685	50	50	50	10.45%	13.27%	19.85%
272	87591	285,576	134.40	135.20	136.80	285,575	133	133	135	1.05%	1.65%	1.33%
681	99213	285,263	98.67	102.12	107.30	285,263	97	100	106	1.72%	2.12%	1.22%
852	97140	284,318	50.58	50.94	50.94	284,318	50	50	50	1.16%	1.88%	1.88%
76	80061	283,682	76.48	86.40	103.04	283,682	75	75	75	1.97%	15.20%	37.39%
774	99213	282,892	91.08	95.91	101.78	282,892	90	95	100	1.20%	0.96%	1.78%
606	80050	280,697	189.75	193.05	197.45	280,695	188	188	195	0.93%	2.69%	1.26%
76	85025	280,464	36.08	36.08	36.08	280,464	35	35	35	3.07%	3.07%	3.07%
77	97110	280,104	67.45	73.09	76.61	280,104	60	62	65	12.41%	17.88%	17.86%
750	95004	277,798	10.18	10.20	10.20	277,798	10	10	10	1.75%	2.00%	2.00%
331	99213	277,798	122.48	127.65	151.80	277,798	120	125	150	2.06%	2.12%	1.20%
604	97110	277,193	70.50	76.61	80.61	277,193	68	68	73	3.68%	12.66%	10.42%
850	99214	276,322	146.50	153.00	161.00	276,322	145	150	159	1.03%	2.00%	1.26%
980	97140	274,502	47.34	48.96	50.94	274,502	47	48	50	0.72%	2.00%	1.88%
370	99213	271,959	94.53	96.95	101.09	271,959	94	95	100	0.56%	2.05%	1.08%
115	99214	269,469	152.50	161.00	178.50	269,469	150	158	175	1.67%	1.90%	2.00%
87	99213	268,913	96.95	101.78	106.26	268,913	95	100	105	2.05%	1.78%	1.20%
606	86003	268,830	29.04	29.59	30.58	268,830	28	29	30	3.71%	2.03%	1.93%
88	97110	268,575	61.34	61.34	66.27	268,575	60	60	65	2.23%	2.23%	1.95%
282	99214	268,464	171.50	178.00	185.50	268,464	168	175	182	2.08%	1.71%	1.92%
926	97110	267,879	61.34	66.04	66.51	267,879	50	50	53	22.67%	32.07%	25.48%
334	99214	267,707	148.00	153.00	158.50	267,707	146	150	155	1.37%	2.00%	2.26%
210	99213	265,254	91.77	96.60	101.78	265,254	90	95	100	1.97%	1.68%	1.78%
208	99213	265,095	101.78	107.30	117.30	265,095	100	105	115	1.78%	2.19%	2.00%
193	83036	264,278	70.20	70.74	72.09	264,278	69	69	71	1.74%	2.52%	1.54%
117	95165	263,757	0.15	0.18	0.19	263,085	18	20	20	-99.18%	-99.08%	-99.06%
336	99213	263,497	96.95	101.09	104.88	263,497	96	100	103	0.98%	1.08%	1.83%
201	97110	263,189	60.40	61.34	66.98	263,189	55	56	56	9.81%	9.53%	19.60%
301	97110	262,547	65.80	66.27	66.27	262,547	65	65	65	1.23%	1.95%	1.95%
272	82248	262,395	27.50	30.91	32.01	262,394	10	10	12	175.00%	209.10%	166.75%
230	99213	262,243	91.08	94.88	95.91	262,243	90	93	95	1.20%	2.02%	0.96%
741	99213	261,604	92.81	100.74	109.37	261,604	91	99	108	1.98%	1.76%	1.26%
606	99214	260,396	174.00	183.50	186.50	260,396	171	181	182	1.75%	1.38%	2.47%
606	99070	260,248	0.08	0.08	0.08	151,137	4	4	4	-98.08%	-98.07%	-98.07%
932	99070	259,930	0.03	0.03	0.03	236,273	3	4	4	-99.01%	-99.20%	-99.15%
926	97140	258,988	55.62	55.98	57.06	258,988	55	55	56	1.13%	1.78%	1.89%
280	99213	258,071	103.16	103.85	104.19	258,071	102	102	102	1.13%	1.81%	2.15%
452	97110	257,503	56.17	59.93	62.75	257,503	50	52	52	12.33%	15.24%	20.66%
155	99213	257,406	76.25	76.59	81.77	257,406	75	75	80	1.66%	2.12%	2.21%
27	99213	255,753	89.70	91.77	95.91	255,753	100	106	120	-10.30%	-13.42%	-20.08%
282	36415	255,249	16.34	17.12	17.19	255,249	16	16	17	2.10%	6.98%	1.11%
641	99213	253,377	89.01	90.74	95.22	253,377	88	89	94	1.15%	1.95%	1.30%
856	99213	252,357	89.70	90.74	101.09	252,357	88	89	100	1.93%	1.95%	1.08%
889	97110	250,354	40.89	45.59	50.53	250,354	40	45	50	2.23%	1.31%	1.05%

81,196,305	84,249,265	2.72%	3.44%	3.40%
		2.72%	3.44%	3.40%
		3.1%	3.7%	3.7%

365. The number of claims used for the MDR product was higher than the number of the claims used for the PHCS product. The reason for the difference is not clear.

366. On average (simple average) MDR percentile values are 2.7% higher than equivalent PHCS percentile values for the 75th percentile, 3.4% higher for the 80th percentile and 3.4% higher for the 85th percentile. When we waited the differences using the number of claims for the CPT/geozip combination weighted average differences the percent differences were 3.1% for the 75th percentile, and 3.7% for the the 80th and 85th percentiles. Given the number of claims involved, the differences are statistically significant at equals p=.01.

367. Moreover, for the 75th percentile the MDR percentile is higher than the PHCS percentile in 179 of the 195 combinations (91% of the time) and are never the same – nine percent are lower. At the 80th and 85th percentiles the MDR percentiles are higher for 182 combinations (92%), never the same and lower in only 14 cases (eight percent). Not only is the MDR higher on average- it is higher for almost every combination in the comparison – systematically.

368. The differences require rejection of the hypothesis that MDR and PHCS produce the same percentile values and require acceptance of the null hypothesis, that they do not produce the same percentile values. The results also suggest that PHCS exhibits systematic downward bias compared to MDR.[109] Which is accurate? Ingenix representatives will not offer an opinion.[110]

369. Since MDR and PHCS use the same data with the same high-low screen processes and the same treatment of modifiers the differences would appear to be attributable to (1) the relative value normalization and (2) the impact of time. If the normalization reduces percentile values (as described above) in MDR that difference would primarily be attributable to the fact that the MDR is more current and includes an inflation adjustment. Indeed, if the derivation process produces downward bias for MDR the relative difference based on inflation would be even greater.

370. Why Ingenix would continue to sell two percentile value products that should accomplish the same purpose is not clear. There have been ongoing internal discussions in the past

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[109] Indeed, the comparison provides for a congruent time analysis. Since PHCS is updated half as often as MDR, the downward bias will be even greater at the end of the PHCS cycles.

[110] Gee Depo. II at 26:6-22. If MDR is accurate PHCS clearly is biased downward so that UCR adjudications based on it are flawed. If PHCS is accurate health insurers are overpaying. Defendants do not generally use MDR.

within Ingenix regarding combining the two products. The reasons for its failure of this project are unclear.

371. In any event, comparison of percentile values in MDR and PHCS suggests that the percentile values produced by the two products are different and that the PHCS shows significant downward bias in comparison with MDR.[111] These findings are consistent with and support the analysis of the contributor data described above.

E. Professor Slottje's bias analysis

372. As noted above, Professor Daniel Slottje has concluded that the high-low screen did not produce downward bias in the Ingenix percentile data. His sole empirical test was to take Ingenix contributor data after the high-low screen, to replace the arbitrarily censored data, in order to observing whether the replacement caused percentile values to increase, remain the same or decrease. The exercise did not purport to justify use of the high-low screen, only to negate suggestions that it would produce downward bias.

373. Professor Slottje found "roughly" that 85% to 88% of the time percentile values did not change and 3% to 6% of the time they actually increased. So, he concluded, there was no evidence of downward bias in the percentile values related to the high-low screen.

374. Contrary to his conclusions, Professor Slottje's findings are fully supportive of downward bias and consistent with the results of the 300 CPT Study and the 350 CPT Study. If 3% of percentile values decreased after replacing the arbitrarily eliminated data and 85% remained the same, 12% of them increased. This actually proves the existence of downward bias relating to the high-low screen. Replacing the data changed percentile values 15% of the time and the ratio of increases to decreases is 4 to 1, consistent with systematic downward bias in percentile values for the high-low screen.

375. As noted above, Professor Slottje fails to report which percentiles he compared. As the 300 CPT Study and the 350 CPT study show, there is little downward bias at the 50th percentile and 60th percentiles and substantial downward bias at the(80th, 85th, 90th and 95th percentiles. It is likely that Professor Slottje's percentile value increases occurred at the high end and that his percentile value reductions occurred at the low end of the distribution.

376. Professor Slottje did not put a dollar value to his findings. Censoring of data at the high and low ends can be expected to provide a much greater dollar reduction at the high end than the increase at the low end. The wider the spread the more disproportionate the impact. The percentile

[111] These differences are not disclosed to clients. Gee Depo. II at 19:9-27:19.

value decreases (12% of the time) for expensive high end billed charges) compared with increases (3% of the time) of very small amounts at the low end may well produce dollar value results where the decreases swamp the increases resulting in substantial downward bias.

377. In short, Professor Slottje's study of the high-low screen, despite his conclusions to the contrary stemming from failure to consider major portions of his findings, is fully supportive of the hypothesis that the high-low screen produces downward bias in the Ingenix percentiles.

378. Most important, the only way to measure downward bias in the PHCS percentiles – as in the 300 CPT Study and the 350 CPT Study - is directly measure percentile values using the contributor data and to compare those values to the PHCS percentiles. Professor Slottje could have done this but did not. His failure to do so means that his study is insensitive to other potential sources of downward bias such as the impact of time, the small numbers issue, derived percentiles, the impact of modifiers and others.

F. Conclusions regarding bias in PHCS.

379. The comparisons of contributor data percentiles to equivalent PHCS percentiles in the 300 CPT Study and the 350 CPT Study find persistent systematic downward bias in the PHCS percentiles-both quantitatively and qualitatively. These findings are verified and confirmed by comparison of MDR with PHCS and by comparison of percentile values in the two studies with one another.

380. What is the extent of the bias? As noted above, bias based on lack of representativeness of the contributor data cannot be ascertained using the contributor data. The contributor data analysis suggest that the extent of this bias may be as much as 6 to 12%.

381. Since MDR and PHCS use many of the same scrubbing processes, the downward bias of PHCS percentile values relative to MDR percentile values (approximately 4%) fails to capture important processes. The bias found by the 300 CPT Study is slightly lower than that indicated by the 350 CPT Study and includes findings relating to dental claims as well as medical and surgical claims. For purposes of a conclusion regarding PHCS downward bias we use the 300 CPT study.

1. Medical surgical claims

382. In order to consider the summary or overall impact of the bias for medical surgical claims we start with the percentile values for the CPT/geozip combinations in the medical surgical contributor data for each of the six comparisons (2006 contributor data with 2005 PHCS version 2, 2006 contributor data with 2006 PHCS version 1, 2007 contributor data with PHCS 2006 version 2, 2007 contributor data with PHCS 2007 version 1, 2008 contributor data with PHCS 2007 version 2, and 2008 contributor data with PHCS 2008 version 1) and weight them by multiplying them by the number of

claims used to derive the values. We do the same for the PHCS percentile values for the corresponding CPT/geozip combinations. We add the weighted percentile values for all of the contributor CPT/geozip combinations and for all of the PHCS CPT/geozip combinations, then divide the PHCS sums by the contributor sums to determine the percentage of the contributor data percentiles represented by PHCS percentiles.

383. Table 29 summarizes the results.

Table 29
Weighted PHCS Percentile Values As Percentage of Contributor Data Percentile Values
Corresponding CPT/Geozip Combinations
From 300 CPT Study

Contributor	2006	2006	2007	2007	2008	2008
PHCS	2005_2	2006_1	2006_2	2007_1	2007_2	2008_1
50th	95.3%	96.9%	90.9%	92.0%	93.5%	95.5%
60th	94.5%	96.2%	89.9%	90.9%	92.7%	94.6%
70th	93.6%	95.2%	88.5%	89.5%	91.4%	93.4%
75th	92.8%	94.5%	87.6%	88.6%	90.6%	92.5%
80th	91.9%	93.4%	86.3%	87.1%	89.4%	91.4%
85th	90.4%	92.0%	84.5%	85.2%	87.9%	89.7%
90th	87.9%	89.4%	81.9%	82.6%	85.6%	87.5%
95th	83.1%	84.6%	76.7%	77.2%	80.8%	82.5%

384. Table 30 shows that PHCS percentiles range from 91% to 97% of the contributor data percentiles at the 50th percentile to 77% to 85% at the 95th percentile.

385. Subtracting these percentages from 100% provides a summary measure of downward bias.[112] Table 30 shows the computation.

Table 30
Downward Bias Estimates
Percentage by Which PHCS Percentile Values are Less Than Contributor Percentile Values
Corresponding CPT/Geozip Combinations
From 300 CPT Study

Contributor	2006	2006	2007	2007	2008	2008	
PHCS	2005_2	2006_1	2006_2	2007_1	2007_2	2008_1	Average
50th	4.7%	3.1%	9.1%	8.0%	6.5%	4.5%	6.0%
60th	5.5%	3.8%	10.1%	9.1%	7.3%	5.4%	6.9%

[112] Essentially similar to weighted average percent differences discussed above although slightly less. We use this calculation for the medical surgical data to be conservative.

70th	6.4%	4.8%	11.5%	10.5%	8.6%	6.6%	8.1%
75th	7.2%	5.5%	12.4%	11.4%	9.4%	7.5%	8.9%
80th	8.1%	6.6%	13.7%	12.9%	10.6%	8.6%	10.1%
85th	9.6%	8.0%	15.5%	14.8%	12.1%	10.3%	11.7%
90th	12.1%	10.6%	18.1%	17.4%	14.4%	12.5%	14.2%
95th	16.9%	15.4%	23.3%	22.8%	19.2%	17.5%	19.2%

386. Table 30 indicates that the downward bias is three to 9% at the 50th percentile and ranges to 15 to 23% at the 95th percentile. We average the percent downward bias for the six comparisons. The averages range from six percent for the 50th percentile to 19.2% for the 95th percentile

387. From claims data provided by Aetna we know the distribution of claim adjudication by percentile level. Most of the claim adjudication occurs at the 80th percentile and the 90th percentile. Table 31 shows the distribution for the 50th through the 95th percentile.

Table 31
Distribution of Percentiles Used for UCR Adjudications
Source: Aetna Claims Data

Percentile	% Adjudications	Weight	Average	Weighted Average
50th	0%	0.00	6.0%	0.0%
60th	1%	0.01	6.9%	0.1%
70th	1%	0.01	8.1%	0.1%
75th	1%	0.01	8.9%	0.1%
80th	58%	0.65	10.1%	6.6%
85th	6%	0.07	11.7%	0.8%
90th	21%	0.24	14.2%	3.4%
95th	1%	0.01	19.2%	0.2%
Total	89%	1.00		11.2%

388. We use the adjudication distribution to develop percentile weights so that we can scientifically develop an overall estimate of downward bias based on the distribution of percentiles used to adjudicate UCR.[113] The column labeled "Weight" in Table 31 shows the weights derived from the distributions

[113] This will be used as an overall summary estimate of downward bias in percentiles used to adjudicate UCR when the data do not permit identification of the percentiles used for the adjudication. Where percentiles used for the adjudication can be identified direct application of the downward bias for the percentile can be used.

389. We develop a weighted average downward bias by multiplying the weights developed in Table 31 to the downward bias percentiles from Table 30. The column labeled weighted average shows the calculation. Overall, the weighted average downward bias, weighted by percentile is 11.2%. Again, this is the overall estimate of downward bias based on internal data processes and does not relate to lack of representativeness.

2. Dental claims

390. Similarly, we develop an estimate for downward bias in dental claims using the 300 CPT study. For this we use the weighted average percent differences from the four contributor data – PHCS product comparisons for which we had PHCS products to permit the comparison.

391. Table 32 summarizes the calculations for dental claims. As with the medical surgical claims we average the percent downward bias estimates by percentile level, apply the weights developed from the Aetna claims data and sum the weights to get a weighted average. The overall weighted average for the downward bias in dental percentiles is 9.8%.

Table 32
Estimate of Downward Bias for Dental Claims

Contrib	Ingenix	50th	60th	70th	75th	80th	85th	90th	95th	Sum
2006	2005_2	8.9%	9.5%	10.0%	10.3%	10.7%	11.1%	12.2%	15.9%	
2007	**2007_1**	**10.6%**	**11.2%**	**11.3%**	**11.5%**	**11.8%**	**11.9%**	**12.4%**	**13.7%**	
2008	**2007_2**	**8.4%**	**9.0%**	**9.2%**	**9.3%**	**9.6%**	**9.9%**	**10.3%**	**11.6%**	
2008	**2008_1**	**5.1%**	**5.5%**	**5.7%**	**5.9%**	**6.2%**	**6.4%**	**6.8%**	**8.0%**	
Average		8.2%	8.8%	9.1%	9.3%	9.6%	9.8%	10.4%	12.3%	
Weights		0.005	0.008	0.012	0.006	0.652	0.070	0.237	0.012	1.000
Weighted	**Average**	0.000	0.001	0.001	0.001	0.062	0.007	0.025	0.001	9.8%

3. HCPCS

392. We did not have products or resources that permitted large scale comparisons of downward bias for HCPCS products. As noted above, the data analysis conducted indicates that the downward bias for the HCPCS products may well be greater than for the medical surgical products. Accordingly, we use the medical surgical overall downward bias estimate of 11.2% for the HCPCS claims.[114]

[114] Available time and resources and availability of PHCS product comparisons did not permit a full study of dental claims, HCPCS claims or anesthesia claims. Ongoing research will focus on them. Similarly, time and resources did not permit quantitative evaluation of the impacts from failure to account for physician specialty and the use of geozips. Additional work will incorporate these concepts as well.

4. Summary of overall estimates of downward bias.

393. In short, using the results of the 300 CPT Study we estimate that the overall downward bias in the PHCS data, exclusive of bias related to lack of representativeness, is 11.2% for medical surgical claims, 9.8% for dental claims and 11.2% for HCPCS claims. Preliminary analysis suggests that an additional six percent to 12% may be a reasonable estimate for downward bias related to the way that the data are collected – over and above the downward bias related to Ingenix issues such as the high-low screen, billed charge inflation, data derivations, modifiers and small numbers issues.

VIII. Damages

394. Between 1998 and continuing to the present, patients and providers submitted claims for reimbursement for out of network medical care to Aetna. Many of these claims were adjudicated using percentile data obtained from Ingenix. The findings from the comparison of the contributor data discussed above suggest that the patients and providers were under-reimbursed as a result of the use of Ingenix percentile data. The under-reimbursement was approximately 11.2% for medical and surgical claims during 2006-2008 and approximately 9.8% for dental claims – exclusive of measures related to interest, lack of representativeness in the data, provider qualifications and training and geographic issues.[115]

395. The downward bias in the Ingenix percentiles suggests measures of damages based on what patients and providers should have been reimbursed "but for" the use of inappropriate percentile data for determining UCR.

396. The consequences of the problems with the Ingenix data are a question of law for the court to determine. The court may determine that the use of percentile data was not appropriate at all for determining UCR and that Aetna should have paid billed charge for all of its claims. Alternatively, the court might determine that use of percentile data for determining UCR would be appropriate if more accurate data were used in which event it could determine that an "accurate allowed charge" amount would provide the best measure of damages.

397. In the first instance the appropriate measure of damages would be the difference between what Aetna should have paid (billed charge) and what it actually paid (allowed amounts based on Ingenix, less adjustments for deductibles, copayments, coinsurance and coordination of benefits). We call this the "billed charge" method for estimating damages.

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[115] We did not have Ingenix products available to compare the HCPCS codes. We estimate that they reflect similar patterns as the dental codes with an overall downward bias of approximately 6.3%.

398. In the second instance, the appropriate measure of damages would be the difference between an "accurate" allowed amount and the amounts paid. We call this the "accurate allowed method."

399. We estimate damages attributable to Aetna's use of the Ingenix percentile data using both approaches. We estimate damages for Aetna's medical claims that were adjudicated using Ingenix[116] (and similar methodologies) and for Aetna's dental claims.

400. In addition to the patient and provider plaintiffs, the Association plaintiffs have expended considerable amounts of time, effort and expense dealing with the out of network UCR system and its problems. The court may determine that they too have been damaged by the biased percentiles and the flawed UCR system. The damage estimates include the expenses that the association plaintiffs have incurred that they would not have been required to expend "but for" defendant Ingenix's development and marketing of percentile data and defendants Aetna's use of it for UCR.

A. Damages related to patients and providers' medical and surgical claims

401. An estimate of damages starts for both methods by identifying out of network claims that were adjudicated using Ingenix. In order to do this we extracted claims from Aetna's medical and claims data and merged the files.[117]

402. The Aetna Medical data contain claim fields that identify standard payment parameters such as billed charge, allowed amounts, deductibles, copayments, coinsurance, coordination of benefits, payment modifiers, paid amounts and procedure codes (CPT).

403. We identified claims adjudicated using Ingenix using "Rating" codes in the data. Where the Rating code was one of the following we concluded (and Aetna representatives agreed) that Ingenix percentiles had been used to adjudicate claims at the percentile expressed in the code:

- HI50AP
- HI70AP
- HI75AP
- HI80AP

[116] Or a similar method such as a percentage of Medicare. Throughout this discussion we incorporate these methods in our concept of "Ingenix."

[117] There appear reasonable and customary adjudication claims in the HMO data but the number of these claims in comparison to the Medical claims is very small and they have not been included in this analysis. Future refinements may incorporate them.

- HI85AP
- HI90AP
- HI95AP
- HI80AN
- HIAA70
- HIAA75
- HIAA80
- HIAA85
- HIAA90
- HIAA95

404. We eliminated claims where billed charge was less than zero, where billed charge was zero, where billed charge equaled allowed (had been paid in full) and where the allowed amount was zero (a denied claim). We also eliminated claims where the billed charge was less than the allowed amount (as erroneous).

405. We developed billed charge less allowed amount) for each claim line[118] summed the difference for each data file for the first step in estimating damage on the basis of billed charge less allowed.

406. We then calculated the percent of allowed amounts paid by Aetna to account for deductibles, copayments and coordination of benefits amounts. We adjusted the difference between what "should have been paid" (billed charge) and what should have been paid but for the adjustments (the allowed amount) by multiplying the percentage of allowed paid by Aetna to account for patient responsibility for deductibles, copayments and coordination of benefits.

407. We used Aetna ACAS medical and claims data for 2001 through 2008. We extracted data with the HI Rating codes for 2001 through 2008 for the analysis. For each year we developed total values for billed charge, allowed, paid amounts, percent of allowed paid, preliminary damage estimate (billed charges less allowed amounts) and the final damage estimate (preliminary damage amount adjusted for the deductibles, copayments and coordination of benefits by multiplying it by the percent paid) . Claims with modifiers that affected payment were not included in the calculations.

1. Billed charge for medical and surgical reimbursement

408. The starting point for the billed charge damage estimation for medical and surgical claims is the total amount that Aetna withheld from patients and providers during the year based on

[118] We found that the field labeled "actual price" more closely reflected the amount actually allowed so we use that field for the "allowed" amount.

UCR. This amount equates to billed charge less allowed for each claim adjudicated using UCR. This is the preliminary damage estimate for the billed charge methodology.[119]

409. We adjusted preliminary damage amount for amounts Aetna's patients were responsible for such as deductibles, copayments and coordination of benefits. For each claim we developed an Aetna "percentage paid" by dividing total amount paid by Aetna to the total allowed amount. We used this percentage to reduce the preliminary damage amount by multiplying it by the percentage paid to compute the final damage amount for which Aetna is responsible.

410. We totaled billed charge, allowed amounts, paid amounts, preliminary damage amounts and final damage amounts for 2001 to 2008. We did not use 2001 since the number of claims lines in 2001 was less than one-fourth the number of claims lines for the other years. If the accuracy of the 2001 data can established we will incorporate the 2001 claims data into the analysis.

411. Table 33 provides a summary of the results of the data extraction and the summation by year.

Table 33
Billed Charge, Allowed Amounts, Percent Paid and Damage Estimates
From Aetna ACAS Medical / Claims Data 2002-2008[120]

	Charges	Allowed	Paid	%Paid	Prelim Est	Damage Est
2008	596,958,161	369,458,027	236,456,463	62.4%	231,749,504	154,733,388
2007	552,699,454	355,581,922	228,504,432	62.9%	201,698,982	135,189,312
2006	528,737,024	347,528,467	227,454,626	64.0%	185,904,493	126,603,311
2005	478,252,015	318,031,809	213,078,856	66.0%	164,354,009	114,752,123
2004	473,660,142	318,691,618	219,394,083	68.0%	159,834,217	114,654,304
2003	482,812,324	327,112,418	233,908,046	70.7%	160,472,722	118,617,031
2002	463,213,149	317,478,220	232,759,415	72.6%	149,920,103	112,614,318

412. The class period has yet to be determined. We estimated damages for 2009 and the first half of 2010. We carry forward the 2008 amount and carry back the 2002 amount. We could have used averages or moving averages but the 2008 and 2002 data are different enough to suggest that it would not be appropriate to do so.[121]

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[119] Mr Frank Cohen, a nationally recognized statistician with expertise in physician billing, provided expert professional services for much of the work involving Aetna damages

[120] Column totals do not mathematically tally as estimates were developed at the claim level and summed.

[121] Again, if 2001 can be established as accurate we will use the 2001 medical / claims data results for 2001, 2000, 1999 and 1998.

413. Table 34 shows the results of the estimation. The total of the Aetna responsible column provides the damages estimate under the billed charge method of determining Aetna's damages for medical claims in the Aetna Medical files.

Table 34
Aetna Medical and Surgical Claims Damage Estimate
Billed Charge Method - 1998-2010

	Charges	Allowed	Paid	%Paid	Prelim Est	Damage Est
	298,479,080	184,729,014	118,228,232		115,874,752	77,366,694
	596,958,161	369,458,027	236,456,463	62.4%	231,749,504	154,733,388
2008	596,958,161	369,458,027	236,456,463	62.4%	231,749,504	154,733,388
2007	552,699,454	355,581,922	228,504,432	62.9%	201,698,982	135,189,312
2006	528,737,024	347,528,467	227,454,626	64.0%	185,904,493	126,603,311
2005	478,252,015	318,031,809	213,078,856	66.0%	164,354,009	114,752,123
2004	473,660,142	318,691,618	219,394,083	68.0%	159,834,217	114,654,304
2003	482,812,324	327,112,418	233,908,046	70.7%	160,472,722	118,617,031
2002	463,213,149	317,478,220	232,759,415	72.6%	149,920,103	112,614,318
2002	463,213,149	317,478,220	232,759,415	72.6%	149,920,103	112,614,318
2002	463,213,149	317,478,220	232,759,415	72.6%	149,920,103	112,614,318
2002	463,213,149	317,478,220	232,759,415	72.6%	149,920,103	112,614,318
2002	463,213,149	317,478,220	232,759,415	72.6%	149,920,103	112,614,318
Total						$1,559,721,139

Italics indicates estimates

414. Aetna's liability for medical and surgical claims based on the billed charge damage estimate (exclusive of interest which will be calculated when the class period is determined), damages related to lack of representative data, damages related to provider qualifications and training and damages related to use of geozips), is $1.6 billion for 1998-2010, an average of $120 million per year.

2. Aetna medical and surgical reimbursement – accurate allowed amounts

415. The second medical and surgical damage estimation is based on a finding that the use of percentage data would be appropriate if it werebased on more accurate percentiles. Here, damages relate to a "but for" world where the percentile values are accurate ones and replace the Ingenix percentile values used in the past by Aetna with the accurate 80th values to produce accurate allowed amounts.

416. In order to estimate damages using this methodology we incorporate our work relating the computation of more accurate percentiles using the Ingenix contributor data described above. Were contributor available for all years we would have used it to develop accurate percentile values for CPT/geozip combinations and would have applied the more accurate values directly. Because sufficient

data are not available we increase the allowed amounts by 11.2%, the composite difference that we found between the contributor data percentiles and the PHCS percentiles in the 300 CPT Study.[122]

417. Once more we extract billed charges, allowed amounts, and paid amounts and compute the percentage of allowed amounts paid by claim – aggregated by year.

418. For this method we also increase the allowed amount by 11.5% to generate an "accurate allowed amount."

419. For claims in which billed charge still was greater than the accurate allowed amount the preliminary damage was the accurate allowed (what would have been reimbursed but for the problem percentiles) less the amount actually allowed.

420. For claims where the billed charge was less than the accurate allowed amount the preliminary damage was the billed charge less the allowed amount since it would have been paid in full if accurate percentiles had been used.

421. Once again we adjusted the preliminary damage amount to account for patient responsibility (deductibles, copayments and coordination of benefits) by multiplying the preliminary damage amount by the percent payment. The result is the final damage estimate for the accurate allowed method.

422. Table 35 shows the results for 2002 to 2008.

Table 35
Billed Charge, Allowed Amounts, Accurate Allowed Amounts, Percent Paid and Damage Estimates From Aetna ACAS Medical / Claims Data 2002-2008

	Charges	Allowed	Accurate Allowed	Paid	%Paid	Prelim Est	Final Est
2008	596,960,161	369,459,665	411,023,879	236,458,101	0.64	97,574,560	67,892,148
2007	552,712,954	355,592,072	395,596,181	228,513,491	0.643	87,147,788	61,186,539

[122] Limited time and resources prevent a full application of the "accurate percentiles." In future iterations of the model, time and resources permitting, we will apply the new accurate percentile for all CPT / geozip combinations for which there are sufficient data to calculate damages claim line by claim line.

2006	528,881,444	347,621,152	386,728,532	227,542,215	0.655	82,371,100	58,332,611
2005	478,322,265	318,053,057	353,834,028	213,089,860	0.67	76,341,523	54,945,402
2004	473,668,745	318,696,781	354,550,170	219,399,182	0.688	81,005,687	59,595,027
2003	482,813,739	327,112,940	363,913,147	233,908,362	0.715	80,934,445	61,830,620
2002	463,213,149	317,478,220	353,194,522	232,759,415	0.733	81,049,977	63,165,002

423. The major difference in Table 35 from Table 33 is the column labeled "Accurate Allowed." These amounts are the result of increasing the allowed amount by the 11.2% factor to correct for downward bias in the percentile data that was used. The Preliminary Estimate here is a combination of amounts from (1) claims where accurate allowed was greater than allowed so that the preliminary estimate was accurate allowed less allowed and (2) claims where billed charge was less than accurate allowed so that the preliminary estimate was the billed charge less the allowed.

424. Once again we applied the percent paid factor to reduce the preliminary damage by the amount for which patients were responsible.

425. Again, we had claims data for 2001 to 2008 but there were so few claims for 2001 as to call into question the validity of the data. Again, we estimated 1998 to 2001 using the 2002 results and 2009 and 2010 by carrying forward 2008 into 2009 and taking half of that amount for the first six months of 2010.

426. Table 36 shows the results of the calculations and the estimations.

Table 36
Aetna Medical and Surgical Claims Damage Estimate
Accurate Allowed Method - 1998-2010

	Charges	Allowed	Accurate Allowed	Paid	%Paid	Prelim Est	Final Est
2010	*231,606,574*	*158,739,110*	*176,597,261*	*116,379,707*	*73.3%*	*40,524,989*	*31,582,501*
2009	*463,213,149*	*317,478,220*	*353,194,522*	*232,759,415*	*73.3%*	*81,049,977*	*63,165,002*
2008	596,960,161	369,459,665	411,023,879	236,458,101	64.0%	97,574,560	67,892,148
2007	552,712,954	355,592,072	395,596,181	228,513,491	64.3%	87,147,788	61,186,539
2006	528,881,444	347,621,152	386,728,532	227,542,215	65.5%	82,371,100	58,332,611
2005	478,322,265	318,053,057	353,834,028	213,089,860	67.0%	76,341,523	54,945,402
2004	473,668,745	318,696,781	354,550,170	219,399,182	68.8%	81,005,687	59,595,027
2003	482,813,739	327,112,940	363,913,147	233,908,362	71.5%	80,934,445	61,830,620
2002	463,213,149	317,478,220	353,194,522	232,759,415	73.3%	81,049,977	63,165,002
2001	*463,213,149*	*317,478,220*	*353,194,522*	*232,759,415*	*73.3%*	*81,049,977*	*63,165,002*
2000	*463,213,149*	*317,478,220*	*353,194,522*	*232,759,415*	*73.3%*	*81,049,977*	*63,165,002*
1999	*463,213,149*	*317,478,220*	*353,194,522*	*232,759,415*	*73.3%*	*81,049,977*	*63,165,002*
1998	*463,213,149*	*317,478,220*	*353,194,522*	*232,759,415*	*73.3%*	*81,049,977*	*63,165,002*
	Total						$ 774,354,857

Italics indicates estimates

427. Aetna's liability for medical and surgical claims based on the accurate allowed damage estimate (exclusive of interest which will be calculated when the class period is determined), damages related to lack of representative data, damages related to provider qualifications and training and damages related to use of geozips), is $774.4 million for 1998-2010, an average of $60 million per year.

B. Damages related to Aetna's Dental Claims

428. Aetna applied reasonable and customary UCR limits to a substantial portion of its dental claims. In many cases it used the Ingenix PHCS dental product. As noted above, Aetna's application of the Ingenix PHCS percentiles provided claims adjudication using percentiles that were biased downward and did not represent comparable charges in the community.

429. The court may make one of two conclusions regarding the use of Ingenix percentiles for UCR in connection with the Aetna dental claims.

- It may conclude that use of the Ingenix percentile data was not appropriate for UCR determinations and, accordingly, Aetna should have been required to reimburse billed charges.
- Or, the court may conclude that use of percentiles would have been appropriate if more accurate percentiles had been used and, accordingly, hold Aetna responsible for reimbursement it would have been required to pay based on the difference between more accurate allowed amounts and the amounts that Aetna allowed using the flawed percentiles.

1. Dental reimbursement should have been made based on billed charge

430. In order to estimate damages where Aetna should have reimbursed billed charges we extracted Aetna's dental claims from the ACAS dental and claim data files. Again, we have these files from 2001 to 2008.[123]

431. Aetna reimbursed providers and patients using an "allowed" amount. For many reasonable and customary claims we understand that this amount was taken from Ingenix percentiles.

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[123] Again, these estimations are subject to refinement and revision as more is learned about the ACAS system. There remain many unanswered questions about how Aetna dental data are compiled and the time period for preparing damage estimates has been very short.

If it is determined that Aetna should have reimbursed billed charge then the basic measure of damages is billed charge less allowed amounts subject to adjustments.

432. In order to estimate billed charge damages we extracted claims that had non zero amounts for billed charges and for allowed amounts (denied claims), non-negative billed charges and billed charges greater than allowed.

433. We eliminated data for claims that were paid in full (billed charge equals allowed) since these claims are not part of the class, and eliminated claims with billed charges of zero. We eliminated claims where the allowed amount is zero on the presumption that these are denied claims and that the claims were denied for reasons other than UCR.

434. We identified RC using "Rating" codes in the data. Where the Rating code was one of the following we assumed that Ingenix had been used at the percentile expressed in the code:

- HI50AP
- HI70AP
- HI75AP
- HI80AP
- HI85AP
- HI90AP
- HI95AP
- HI80AN
- HIAA70
- HIAA75
- HIAA80
- HIAA85
- HIAA90
- HIAA95

435. We developed billed charge less allowed amount) for each claim line, summed the difference for each year for the first step in estimating damage on the basis of billed charge less allowed. Likewise, we extracted the allowed amount (the actual price) for each claim and summed them for the year.

436. We then calculated the percent of allowed amounts paid by Aetna to account for dental deductibles, copayments and coordination of benefits amounts. We developed a percentage paid by dividing the paid amount by the allowed amount and used this to adjust preliminary damages for patient responsibility. We adjusted the difference between what "should have been paid" (billed charge) and what should have been paid but for the adjustments (the allowed amount) by multiplying the percentage of allowed paid by Aetna to account for patient responsibility.

437. The results are shown in Table 37.

Table 37
Aetna Dental Claim Extractions
Based on "Billed Charge Reimbursement
Aetna ACAS Dental Files

	Billed	Allowed	Paid	%Paid	Prelim Est	Final Est
2008	596,960,161	369,459,665	236,458,101	62%	231,749,866	154,733,750
2007	552,712,954	355,592,072	228,513,491	63%	201,702,332	135,191,624
2006	528,881,444	347,621,152	227,542,215	64%	185,956,228	126,650,107
2005	478,322,265	318,053,057	213,089,860	66%	164,412,348	114,810,322
2004	473,668,745	318,696,781	219,399,182	68%	159,837,657	114,657,726
2003	482,813,739	327,112,940	233,908,362	71%	160,473,615	118,617,371
2002	463,213,149	317,478,220	232,759,415	73%	149,920,103	112,614,318

438. The column "Billed" is a summation of the billed charges for the year. Allowed amounts are the amounts Aetna allowed on the basis of UCR using the Ingenix percentiles. The difference, the Preliminary Estimate of damage, is the difference between billed charges and allowed amounts. The "Final Estimate" column sets forth the portion of the difference that is Aetna's responsibility after adjusting for deductibles and copayments by multiplying the percent paid.

439. The ACAS files do not provide data for 1998-2000 or for 2009 and 2010. Again, the 2001 amount is suspect. We estimate amounts for 2009 and 2010 using 2008. We estimate 1998-2001 based on 2002.[124] Table 38 shows the results of the estimation.

Table 38
Aetna Dental Claim Damage Estimation
Based on "Billed Charge Reimbursement

	Billed	Allowed	Paid	%Paid	Prelim Est	Final Est
2010	*298,480,080*	*184,729,833*	*118,229,051*	*62%*	*115,874,933*	*77,366,875*
2009	*596,960,161*	*369,459,665*	*236,458,101*	*62%*	*231,749,866*	*154,733,750*
2008	596,960,161	369,459,665	236,458,101	62%	231,749,866	154,733,750
2007	552,712,954	355,592,072	228,513,491	63%	201,702,332	135,191,624
2006	528,881,444	347,621,152	227,542,215	64%	185,956,228	126,650,107
2005	478,322,265	318,053,057	213,089,860	66%	164,412,348	114,810,322
2004	473,668,745	318,696,781	219,399,182	68%	159,837,657	114,657,726
2003	482,813,739	327,112,940	233,908,362	71%	160,473,615	118,617,371

[124] Data for 2001 shows much lower levels of use of Ingenix in that year. Additional investigation may reveal data production errors for those years at which time the damage estimates will be revised.

2002	463,213,149	317,478,220	232,759,415	73%	149,920,103	112,614,318
2001	*463,213,149*	*317,478,220*	*232,759,415*	*73%*	*149,920,103*	*112,614,318*
2000	*463,213,149*	*317,478,220*	*232,759,415*	*73%*	*149,920,103*	*112,614,318*
1999	*463,213,149*	*317,478,220*	*232,759,415*	*73%*	*149,920,103*	*112,614,318*
1998	*463,213,149*	*317,478,220*	*232,759,415*	*73%*	*149,920,103*	*112,614,318*
	Total					$ 1,559,833,116

440. If Aetna should have paid billed charge the final estimated damage amount is $1,559,833,116 – $780 million per year.

2. Dental reimbursement based on accurate allowed amounts

441. In the alternative, the court may determine that Aetna should have reimbursed based on more accurate allowed amounts. As was the case with medical and surgical claims, we develop an accurate allowed amount by increasing allowed amounts using the downward bias estimate of 9.8% for dental claims determined in the 300 CPT Study described above.

442. For the dental claims (like the medical claims) we computed an "accurate allowed amount" equal to 1.098 * allowed. The preliminary damage estimate is accurate allowed less allowed where the billed charge is greater than the accurate allowed and billed charge less allowed amount where the billed charge is less than the accurate allowed amount.

443. Again, we adjust the preliminary estimate by the percent paid factor to reflect deductibles, copayments and coordination of benefits.

444. Table 39 summarizes the extractions and calculations.

Table 39
Billed Charge, Allowed Amounts, Accurate Allowed Amounts,
Percent Paid and Damage Estimates
From Aetna ACAS Dental / Claims Data 2002-2008

Year	Billed	Allowed	Paid	%Paid	Prelim Est	Final Est
2008	1,121,478,978	960,956,166	649,322,954	62.4%	85,613,109	58,006,008
2007	1,096,780,260	937,753,449	632,525,770	62.9%	68,437,199	47,646,048
2006	1,053,613,563	897,579,706	606,512,772	64.0%	85,379,983	57,383,027
2005	1,038,002,965	885,239,811	593,364,621	66.0%	87,553,705	58,050,374
2004	942,128,360	803,104,275	535,316,394	68.0%	84,828,743	56,522,445
2003	900,255,524	761,926,417	510,571,059	70.7%	71,135,653	47,572,081
2002	750,089,102	636,444,922	429,550,946	72.6%	59,158,183	40,218,017

445. Once again we estimate 2009 and 2010 as well as 1998 to 2001 using 2008 and 2002 as references in order to generate final damage amounts attributable to dental claims using the accurate allowed method. Table 40 summarizes the results.

Table 40
Aetna Dental Claims Damage Estimate
Accurate Allowed Method - 1998-2010

Year	Billed	Allowed	Paid	%Paid	Prelim Est	Final Est
2010	560,739,489	480,478,083	324,661,477	62.4%	42,806,555	29,003,004
2009	1,121,478,978	960,956,166	649,322,954	62.4%	85,613,109	58,006,008
2008	1,121,478,978	960,956,166	649,322,954	62.4%	85,613,109	58,006,008
2007	1,096,780,260	937,753,449	632,525,770	62.9%	68,437,199	47,646,048
2006	1,053,613,563	897,579,706	606,512,772	64.0%	85,379,983	57,383,027
2005	1,038,002,965	885,239,811	593,364,621	66.0%	87,553,705	58,050,374
2004	942,128,360	803,104,275	535,316,394	68.0%	84,828,743	56,522,445
2003	900,255,524	761,926,417	510,571,059	70.7%	71,135,653	47,572,081
2002	750,089,102	636,444,922	429,550,946	72.6%	59,158,183	40,218,017
2001	750,089,102	636,444,922	429,550,946	72.6%	59,158,183	40,218,017
2000	750,089,102	636,444,922	429,550,946	72.6%	59,158,183	40,218,017
1999	750,089,102	636,444,922	429,550,946	72.6%	59,158,183	40,218,017
1998	750,089,102	636,444,922	429,550,946	72.6%	59,158,183	40,218,017
	Total					$ 613,279,080

446. Table shows that the final damage estimate for Aetna dental claims using the accurate allowed approach is $613 million, approximately $47 million per year exclusive of interest and damages related to data representativeness, provider qualifications and training and the use of the geozips.

C. Damages related to lack of representativeness

447. As discussed in detail above, lack of representativeness in the contributor data may be responsible for additional downward bias of 6 to 12%. These damages would not apply if the billed charge method is used to determine damages. However, if the accurate allowed amount method of damage estimation is used it would be appropriate to increase the accurate allowed damage estimates by one half to reflect problems relating to lack of representativeness of the Ingenix contributor data.

448. In this case it would be appropriate to add approximately $387 million to the damage estimate for medical and surgical claims based on the accurate allowed methodology. It would be appropriate to add approximately $306 million to the damage estimate for dental claims based on the accurate allowed methodology.

D. Damages related to failure to consider provider training and qualifications

449. As noted above, the Ingenix percentile data do not adjust the billed charge percentiles for provider training and qualifications. Defendants' experts and Ingenix employees claim that it is not possible to develop this degree of detail using the contributor data. However, the impossibility relates more to the statistical approach used by Ingenix then to the potential for accurate reflection or adjustment of billed charge percentiles based on training and qualifications.

450. It is possible to model the relationship between billed charges and provider qualifications in a meaningful way that permits a damage estimation based on the models.

E. Damages related to use of geozips for geographic measures

451. Previous discussion has shown that it is not appropriate to use the geozip for a community, area or geographic market when using percentile data for UCR adjudication. Defendants experts contend that use of any smaller area will make it impossible to provide percentile values because of the number of CPT/geography combinations will proliferate beyond manageability.

452. Such a view relates to the premise that geographic factors must be applied directly in a nonparametric fashion to produce percentile values. This approach has not been adopted by others in their development of payment methodologies.

453. Rather, Medicare has devised a "GCPI" system of geographic adjustment (geographic practice cost adjustment) that consists of 80 distinct Medicare payment localities nationwide. The GAO has studied the GCPI system in detail and concluded that the indices are valid in design although data and methods used for calculation are in need of refinement. (United States Government Accountability Office, 2005).

454. The physician fee reference data used by defendants' experts including Physician Fee Reference, MAG Mutual and PMIC, all use geographic adjustment factors. Even Ingenix has developed geographic adjustment factors.

455. Accordingly, if the court were to determine that use of percentile data would be appropriate for UCR adjudication if accurate percentile values were used, and accurate allowed damages approach, it would be appropriate to develop and implement geographic adjustment factors that improve the use of the geozip as a geographic surrogate for "community" or geographic market.

456. Available time and resources have been limited in the development of damage estimates. There has not been time to develop geographic adjustment or to estimate damages related thereto. Future work and refinements will provide them. An approach that may have substantial utility would be two develop adjustment factors that relate to build charge (price level) adjustment for

subdivisions of the geozip whether at the zip code level or for logical groupings of zip codes developed using statistical techniques such as spatial analysis.

F. Association damages

457. In addition to damages suffered by patients and providers, plaintiff medical associations and societies have expended time and incurred other expenses dealing with the out of network payment issues underlying this litigation.

458. In order to estimate Association plaintiff damages we conducted an informal survey of the Association plaintiffs.

a. The American Medical Association uses 15% of an executive vice president's time and approximately 55% of an FTE (multiple staff) on an annual basis.

b. The American Podiatric Medical Association has inurred $245,000 related to time and expenses for staff, committee meetings, regional meetings, forums, and consultants.

c. The Connecticut State Medical Society has incurred $410,000 for staff, consultants, outside counsel and lobbyists.

d. The Florida Medical Association used five hours of a director's time per year.

e. The Medical Association of Georgia had 50 hours total time from its director and three hours total time from a staffer.

f. The Medical Society of New Jersey has incurred $49,000 in expense from an expert and 70% FTE of (multiple) executive staff members annually.

g. The Medical Society of the State of New York annually devotes 0.86 of an FTE among a variety of staff including the executive vice president, senior vice president, vice presidents, directors and staff.

h. The New Jersey Psychological Association devotes 45% of an FTE director annually to these issues on an annual basis.

i. The North Carolina Medical Society uses .55 of an FTE for several employees annually including General Counsel, associate general counsel and director of legislative affairs.

j. The Texas Medical Society employs nearly one full FTE for various staffers, vice presidents and directors on these issues annually.

459. We estimate salary and benefits at the executive vice president level of $400,000 per year, general counsel and senior vice president at $200,000 per year, vice president at $150,000 per year, directors at $100,000 per year and staff at $35,000 per year.

460. Using the informal survey responses we estimate the staff costs and other expenses incurred by the Association plaintiffs. Table 41 summarizes them.

Table 41
Damage Estimates for Association Plaintiffs
Data Source: Informal Survey

	2004	2005	2006	2007	2008	2009	2010	Not allocated	Total
AMA									320,125
Executive - 15%	30,000	30,000	30,000	30,000	30,000	30,000	15,000		
Staff - 55%	19,250	19,250	19,250	19,250	19,250	19,250	9,625		
Amer Pod Med Assn									245,000
								245,000	
Conn State Med Soc									410,000
								410,000	
Florida Med Assn									9,750
Personnel	1,500	1,500	1,500	1,500	1,500	1,500	750		
									15,150
Med Assn Georgia								15,150	
Med Soc New Jersey									190,898
Consultant						48,710			
Staff	21,875	21,875	21,875	21,875	21,875	21,875	10,938		
Med Soc State New York									746,525
Executives and staff	114,850	114,850	114,850	114,850	114,850	114,850	57,425		
New Jersey Psych Assn									292,500
Directors (0.55 FTE)	45,000	45,000	45,000	45,000	45,000	45,000	22,500		
North Carolina Med Soc									474,500
	73,000	73,000	73,000	73,000	73,000	73,000	36,500		
Texas Med Soc									667,400
Personnel	98,300	95,300	98,000	96,600	102,600	110,050	66,550		
Totals	403,775	400,775	403,475	402,075	408,075	464,235	219,288	670,150	$3,371,848

461. As Table 41 illustrates, Association plaintiff damages are in the general range of $400,000-$460,000 per year. The total damage estimate for 2004 through June of 2010 is $3.4 million.

G. Summary of damage estimates

462. In short, we have estimated damages using both the billed charge method and the accurate allowed method. The court could determine that use of percentile data for UCR determinations is not appropriate. In that eventuality billed charge method for damage estimation would be appropriate. If the court determines that accurate percentile values should have been used for UCR determinations, the accurate allowed method would permit estimation of damages in a "but

for" world where accurate percentile values were developed. Finally, we have estimated the damages incurred by the Association plaintiffs.

463. Table 42 summarizes these damage estimations. Damages fall in two categories: Increased reimbursement for past claims using either the billed charge method or the accurate allowed method, and Association damages.

Table 42
Overall Summary of Damage Estimation

	Medical surgical	Dental	Total
Billed charge method	$1,559,721,139	$1,559,833,116	$3,119,554,255
Accurate allowed method			
Accurate allowed adjustment	$774,354,857	$613,279,080	$1,387,633,937
Representativeness	387,177,429	306,639,540	693,816,969
Total	$1,161,532,286	$919,918,620	$2,081,450,906
Association damages			$ 3,371,848

464. The first category is designed to make whole patients and providers who were under-reimbursed by Aetna using PHCS percentiles. The first category is designed to reflect two different views of increased reimbursement: (1) increased reimbursement based on billed charges in the event that the court were to determine that it was not appropriate to use percentile data for UCR determinations and that Aetna should have paid billed charges for out of the network medical care or (2) increased reimbursement based on "accurate allowed" amounts developed with reference to more accurate percentile tables (reversing downward bias found in the 300 CPT Study and in the 350 CPT Study). Under the first, Aetna's total damages for 13 years of under-reimbursement would be $3.1 billion. Under the second, Aetna's total damages would be $2.1 billion. After the determination of the class period an appropriate interest calculation will be added. The second category, while small in a relative sense, provides important recognition of the efforts of the Association plaintiffs in dealing with the out of network provider reimbursement issues.

IX. Conclusions

465. This report has investigated issues that have arisen in connection with the production by Ingenix of percentile data tables relating to billed charges for medical care services and their use by Aetna to adjudicate out of network reimbursement to patients and providers.

466. The issues that have been investigated include the representativeness of data used to produce the percentiles, the use of a high-low screen to censor or eliminate data, the inclusion of claims with payment modifiers in the data, confidence issues relating to small numbers problems where percentiles were constructed using very limited data, derived percentiles that fail to reflect billed charges in a community, the failure to consider provider qualifications and training, much less experience in developing the percentile data, the use of broad geographic areas called geozip that fail to reflect a community or medical services market and failure to recognize and account for billed charge inflation over time.

467. Extensive empirical analysis has determined that there are problems with the percentile data in theory. The existence and likely impact of these problems have been illustrated with real data from health insurers and Ingenix.

468. The analysis has used to independent studies of the contributor data, a comparison of MDR and PHCS percentiles and reports by defendants experts to show the existence and extent of systematic downward bias in the percentile data provided by Ingenix. Overall, the downward bias appears to be approximately 11.2% for medical surgical claims and 9.8% for dental claims.

469. We have calculated amounts that would make whole patients, providers and Associations based on reimbursement of billed charges should the court determined that use of percentile data for UCR adjudication was not appropriate at all, or development of "accurate allowed amounts" that increase reimbursement in proportion to the downward bias in the percentiles, as well as reimbursement for time and expense incurred by the Associations in dealing with these issues. The "accurate allowed" approach adopts the very method of adjudicating claims used by Aetna. It merely replaces a flawed allowed amount with an accurate allowed amount – claim by claim.

470. The challenges of dealing with 1.4 billion medical care claims for each year have been great. More and better data, as always, can improve results efforts are ongoing to clarify and refine findings relating to downward bias and damages.

471. Ingenix produced and sold billed charge percentile data tables that were developed without scientific justification. Aetna adopted those tables for its UCR adjudication. The process under reimbursed consumers and providers and required substantial efforts from the Associations. The damages calculated provide a reasonable remedy.

***

472. For my work on this matter I am being compensated at the rate of $350 per hour. My compensation is not contingent on the outcome of the case.

Submitted August 9, 2010

Stephen Foreman

Stephen Foreman, PhD, JD, MPA

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Exhibit A Curriculum Vitae

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Academic qualifications

1994	Ph.D.	Univ. of California, Berkeley	Berkeley, CA
1988	M.P.A.	Harvard University	Cambridge, MA
1975	J.D. Honors	University of North Carolina	Chapel Hill, NC
1972	A.B. High Honors	North Carolina State University	Raleigh, NC

September 2004 to present	**Robert Morris University, Pittsburgh, PA** **Associate Vice President for Academic Affairs (2006-2008)** **Department Head, Allied Health (2004-2006)** **Associate Dean Research (2005-2007)** **Associate Professor of Economics and Health Policy** **Crimea State Medical University, Simferopol, Crimea, Ukraine (2008-present)** **Professor, Social Medicine and Health Economics** **Syracuse University, Syracuse, NY (2010-prst)** **Senior Research Scientist**

Honors and awards

- 2008-2009 US State Department Fulbright Scholar: lectures in health policy, Crimea State Medical University
- Diplom, Honorary Professor, Crimea State Medical University, 2009
- Pennsylvania Chapter, American College of Emergency Physicians, Service to Emergency Medicine, 2006
- Robert Morris University Student Government, Distinguished Faculty Teaching Award, 2007
- Robert Morris University Student Government, Service to Students Award, 2006

Administrative responsibility:

- Curriculum and curriculum development: worked with graduate curriculum committee, undergraduate curriculum committee and Deans' council.
- New program development, planning, budgeting, Pennsylvania Department of Education application and review.
- Pennsylvania Department of Education program approval compliance.
- Externally funded research including research design, grant applications, budgeting and grant administration.
- Institutional Review Board.
- Accreditation organizations.

- Participant, University President's Cabinet and Deans' Council.
- Academic risk dashboard responsibility for institutional risk management.
- Significant accomplishments
  - Collaboration with faculty members to expand funded research programs.
  - Pioneering STEM program grant awarded by National Science Foundation to School of Engineering, Mathematics and Science.
  - External funding program for research and academic activity expanded significantly in 2007 and 2008.
  - Development, coordination within the university, submission, and Pennsylvania Department of Education approval for a School of Osteopathic Medicine and programs in Doctor of Nursing Practice, Bachelor of Science in Healthcare Administration, Bachelor of Science in Nuclear Medicine and Bachelor of Science in Biology.
  - Worked with Pennsylvania Department of Education representatives to restructure the industrial engineering program.
  - Helped prepare the academic portions of the University's 2007-2012 Strategic Plan.
  - Prepared and obtained graduate curriculum committee approval of academic standards and support for online courses and degrees.
  - Worked with deans and finance representatives to revise the University's research grant application guidelines.
  - Developed demand studies for new programs in medicine, nursing and allied health.
  - Prepared economic impact analysis for College of Osteopathic Medicine and Doctor of Nursing Practice programs.
  - Developed a structure for a College of Health Sciences.

Teaching:

- Faculty appointments: School of Business and School of Nursing and Health Science.

- Lecturer, social medicine and public health, medical law, Crimea State Medical University, Simferopol, Crimea, Ukraine
  - Courses taught: health economics, health policy, health law and ethics, health care finance, principles of macroeconomics, principles of microeconomics, intermediate macroeconomics, statistics and quantitative methods.
  - Development and implementation of course level outcome assessment using nationally normed economic simulation.
  - Consistently excellent teaching evaluations.

Research and scholarly areas of interest (peer reviewed publications attached):

- International aging, international business competition and incentives to care for the elderly.
- Comparative international health care management.
- Comparative international health systems.
- Optimal government and private funding for health care.
- Determinants of corruption.
- Physician, hospital and health insurance markets: market structure and performance, physician manpower, workload and patient safety.
- Trilateral monopoly and countervailing power in the market for health insurance.
- The economic impact of Medicaid spending and health outcomes.

- Patient safety. Use of Poisson regression to predicting hospital based infections, falls, adverse drug reactions and surgical errors.
- Referee for scholarly journals and publishers including International Academy of Business and Economics, Journal of Health Policy, Politics and Law and Oxford University Press.

Service:

- Robert Morris University Strategic Planning Council.
- Chapter Advisor, Robert Morris Phi Delta Theta fraternity.
- Advisor, Pennsylvania Chapter, American College of Physicians.
- Pennsylvania Task Force on Health Care Reform, appointed by Governor Edward Rendell.
- State of New York, Office of the Attorney General, health insurer data issues.
- American Civil Liberties Union.Report on the economic impact of a civil union constitutional amendment.
- Heritage Valley Health System Patient Safety Committee.
- Review committee chair / program reviewer for the Pennsylvania Department of Education. Reviews of academic programs at Immaculata University and application for University status by Miseracordia College.
- National Consortium of Regional Healthcare Initiatives.
- Professional addresses, testimony and reviews including:

o Ohio Valley Hospital Strategic Planning Retreat, October 2009.

o Special lecture series on health policy for the faculty of Crimea State Medical University. November 2008.

o Pennsylvania Insurance Department hearings on proposed merger of Highmark and Independence Blue Cross. July 2008.

o Pennsylvania Association of Medical Suppliers, "The Impact of Competitive Bidding for DME." August 2008.

o Mercer County Medical Society, "International Health Care Systems." April 2008.

o Mercer County Hospital, "International Health Care Systems." July 2008.

o Grove City Hospital Annual Planning Retreat, "The State of Medicine in Pennsylvania." May 2008.

o Monroeville Chamber of Commerce, "The US Macroeconomy." March 2008.

o Hospital Council of Western Pennsylvania, "The State of Medicine in Pennsylvania" (November 2007).

o Beaver County Medical Society, "Overview of National Patient Safety Programs" (October 2007).

o Pennsylvania Healthcare Association, "The Future of Long Term Care" (August 2007).

o Grand Rounds for

  - Pinnacle Health System (December 2004 and January 2007)(health professions manpower) and
  - Western Pennsylvania Hospital (June 06)(medical errors as a nonlinear event)

o Keynote speaker, Cong. Joseph Sestak, Health Care Forum – "Health Professions Manpower" (June 2007)

o New Jersey legislature (physician payment in New Jersey) (January 2007) and the New Jersey Insurance Department (May 2007)

- Speaker on patient safety for Jewish Healthcare Foundation of Pittsburgh's Patient Safety Fellows program (June 2007) (The "conspiracy of silence")
- Invited participant, PaACEP Town Hall Meeting: Emergency Medicine in Pennsylvania (May 2007)
- PaACEP Scientific Conference, "Emergency department staffing in Pennsylvania" (Nov 2007)
- Keynote speaker for the Pennsylvania Primary Care Forum (May 2007)
- Keynote speaker, Annual Planning Meeting, PCIM, "Nurse practitioners and money" (June 2007)
- Keynote speaker for the Hawaii Medical Association annual meeting (Oct 2006)(payment for performance)
- World VistA annual meeting: the Economics of World VistA" (April 2007)
- Washington State Medical Association annual meeting, "Payment for Performance" (June 2006)
- Southwestern Pennsylvania Academy of Surgeons, the 'State of Medicine in Pennsylvania" (Sept 2006)
- Pennsylvania Medical Group Management Association, the 'State of Medicine in Pennsylvania" (June 2006)
- Delaware Valley Medical Society, the 'State of Medicine in Pennsylvania" (June 2006)
- Beaver County Medical Society, "Odds, risks and nonlinearity in Patient Safety" (Oct 2006)

Selected consulting and advising:

- Special consultant to the contract monitor for the FAIR Health project, New York Attorney General.
- 2009-present: Delaware Valley Health Care Coalition, negotiating committee member for health care services for 200 labor unions.
- 2009-present: Delaware Valley Health Care Coalition, quality hospital project – identification of hospital quality and efficiency.
- 2009-present: Ajamie, LLP. Physician payment litigation.
- 2009- present: Zumpano, Patricios and Winker, Coral Gables, FL: physician payment litigation.
- 2009 –present: Post and Post, insurance antitrust litigation.
- 2007-present: Ohio Valley Hospital, Pittsburgh, PA: strategic planning consultant.
- 2008-2009: Attorney General, State of New York, matters relating to physician payment and health insurance data.
- 2008-present: Medical Society of New Jersey: conversion of Horizon Blue Cross to for profit status.
- 2008-present: Leech, Tishman, Pittsburgh, PA. Hospital and physician markets in Southwest Pennsylvania.
- 2007-2008: Dominion, Economic impact of energy distribution.
- 2006-present: New Jersey Medical Society, economic and legal implications of proposed physician fee schedules.
- 2006-2007: Pennsylvania College of Internal Medicine, Pennsylvania Association of Primary Care Physicians and Pennsylvania Academy of Pediatrics. The market for primary care in Pennsylvania.
- 2006-2007: Pennsylvania College of Internal Medicine, the economic impact of a primary care physician loan forgiveness program on the Pennsylvania economy.
- 2006-2007: Pennsylvania Medical Society, structure and conduct in the markets for health insurance, hospital services and physician services in Pennsylvania.

- 2005-2007: Walters, Bender et al, Kansas City, MO. Simulation of damages related to physician payment system.
- 2006-2007: American College of Obstetricians and Gynecologists, obstetrician access in the US.
- 2005-2006: DeForest, Kocelnik, Pittsburgh, PA. Damage modeling involving intentional interference with contractual relations in long term care settings.
- 2005-2006: Throckmorton, Tropin, Coral Gables, FL. Economic model of profits, administrative costs and CEO salaries in health insurance firms.
- 2004-2007: Pennsylvania Medical Society, professional manpower issues, medical liability and health insurance markets.
- 2004-2006: Whatley, Drake, et al, Birmingham, AL. Multidistrict Class Action Litigation, health insurance market structure and conduct.
- 2003: Mattis, Baum, Rizza, O'Connor, Pittsburgh, PA. Economic impact of malpractice liability on the market for obstetrical services in southwestern Pennsylvania.
- 2003: Pennsylvania Medical Society, economic impact studies of liability awards on the market for physician services.
- 2001-2007: American Medical Association, structure and performance in the market for physician services.
- 2002: Jones, Day, structure and concentration in Central Pennsylvania insurance markets.

2001-2004 **Vice President, Research, and Director, Pennsylvania Medical Society Health Services Research Institute, Harrisburg, PA**

Primary Duties: Policy research relating to the medical care and health insurance industries.

- Areas of emphasis:markets for physician services, health insurance and liability insurance markets, medical manpower, access to care and patient safety, Medicare and Medicaid funding, the economic impact of liability reform and transportation economics.

Reports regarding organization and operation of physician markets.

- Competition in Health Insurance: A Comprehensive Study of U.S. Markets, AMA (2002).
- The Economic Impact of the Campbell Bill, AMA (1999).
- Health Insurance and Medical Care Markets in Southeast Pennsylvania, Pennsylvania Medical Society (2002).
- Health Insurance and Medical Care Markets in Western Pennsylvania, Pennsylvania Medical Society (2003).
- Premium Deceit, A Critique of a Center for Justice and Democracy Study, Pennsylvania Medical Society (2003).
- Some Selected Comments About Public Citizen 'Medical Misdiagnosis' Reports and Retorts Using National Practitioner Data Bank information, Pennsylvania Medical Society (2003).
- The Economic Impact of Tort Reform in Pennsylvania (1998), Pennsylvania State University Working Paper (1998).

Managed the Medical Society's research budget.

Testified before and drafted reports for legislative and regulatory bodies at the state and national level.

- Testimony and Report on behalf of the Pennsylvania Medical Society for 2004 Antitrust Hearings before the US Senate Judiciary Committee, Subcommittee on Competition,

- Testimony and Report on behalf of the American Medical Association for 2003 Federal Trade Commission and Department of Justice Hearings on Health Care Competition Law and Policy,
- Testimony and Report on the economic impact of a proposed class action settlement involving Pennsylvania physicians in the Philadelphia Court of Common Pleas,
- Testimony and Report regarding the Economic Effect of Caps on Liability Awards on behalf of the Pennsylvania Medical Society before the Pennsylvania Legislature,
- Testimony on behalf of the Pennsylvania Medical Society at 2002 FTC and Justice Department Hearings on Health Care Competition,
- Testimony regarding the economic impact of "State Action" antitrust legislation before the Pennsylvania legislature,
- Testimony and Report regarding the Economic Impact of Tort Reform before the Pennsylvania legislature on behalf of the Pennsylvania Civil Justice Coalition,
- Testimony regarding perinatal care hospital regulation before the Ohio legislature on behalf of Grandview Hospital, Dayton, Ohio,
- Testimony and Report before the Pennsylvania Attorney General and the Pennsylvania Department of Insurance regarding the proposed merger of Blue Cross of Western Pennsylvania and Pennsylvania Blue Shield on behalf of the Pennsylvania Medical Society,
- Testimony and Report for the Pennsylvania Department of Insurance regarding market concentration in Southeast Pennsylvania,
- Presentation of a report to the U.S. Centers for Medicare and Medicaid Services
- Report regarding the impact of physician fee increases on access to Medicaid services in California in preparation for litigation in the California District Court regarding the adequacy of Medicaid payment.
- Report regarding damages for the Arizona Attorney General in a matter regarding alleged collusion among Phoenix nursing home operators.

Frequent speaker before professional and community organizations.

Guest lecturer for academic institutions including the University of Pennsylvania and the Pennsylvania State University School of Medicine.

Developed research institute consulting clients that included the American Medical Association, major antitrust law firms, major class action law firms, state medical societies and various professional organizations.

1994-2001 **Assistant Professor,** **Pennsylvania State University**
State College, PA

Honors and awards:

- Mortarboard Society Award -- outstanding University professor of 1996.
- 1996 Article named to International Management Association's "Hall of Fame"
- 1992 Edgar Hayhow Award winner for "The Power of Value-Adding Partnerships" from the American College of Healthcare Executives.

Teaching:

- Courses taught: Doctoral candidates, master's students and undergraduate courses in health economics, health care finance, statistics, research methods, quantitative analysis, time series methods and health law and ethics.
- Supervised doctoral and master's thesis preparation and undergraduate honors students.
  - Chair for three Ph.D. candidates

- Committee member for 12 Ph.D. candidates
- Thesis Advisor for 10 Master's students
- Thesis advisor for five undergraduate honors students.

- Significant accomplishments
  - Consistently received the highest teaching evaluations in the Department, the College and the University.

Service:

- University Insurance and Benefits committee.
  - Monitoring and managing a $64 million benefits program and development of a strategic benefits plan
- College Scholarship Committee.
  - The award of scholarships to undergraduates and graduate students.
- Department Ph.D. committee.
- Frequent speaker before governmental bodies and professional associations.

Research and scholarly activity:

- Refereed scholarly publications.
- Principal investigator for funded research projects including economic impact analysis of state legislative efforts, demand for health services and quantitative research design.
- Referee for a number of scholarly journals
- Recognition for outstanding scholarly work:

1989-1994 PhD. Program, Teaching Associate, Lecturer and Senior Research Associate, The University of California, Berkeley

Koford Memorial Fellow.
Agency for Health Care Quality and Research Fellow.
Dissertation research on incentive payment systems in health care. Dissertation completed in June 1994.
Teaching assistant: econometrics and organizational theory.
Course work in a variety of disciplines including economics, health economics, game theory, quantitative methods including ARIMA time series analayis, organizational theory (micro and macro) and finance.
Supervised research relating to time series analysis, incentive payment systems, managed care and others.
Managed research and training grants for The Robert Wood Johnson Foundation, the Agency for Health Care Quality and Research and the National Institute for Aging.
Contract research projects included projects for the Blue Cross and Blue Shield Association, Arizona Nursing Home Association and the Institute of Medicine.
Published work in scholarly journals.
Performed economic analyses for antitrust cases - Arizona nursing homes (damages), Medicaid dental payment in California (access to care and dentist payment elasticity of supply) and Blue Cross payment (time series analysis).

1987-1988 Master's Program, Harvard University

Completed in course work in a number of fields including negotiation, labor management, economics and game theory.
Master of Public Administration degree received, June 1988
Lucius Littauer Fellow –honors for outstanding academic performance and leadership

1985-1987 President & CEO, St. Benedict's Health System, Ogden, Utah

Responsible for all phases of operations of a multi-institutional health system located in the Intermountain west with 800 employees. Facilities included owned and managed hospitals, alcohol and chemical treatment facilities, ambulatory surgical facilities, free standing psychiatric centers and other behavioral health facilities.

Successfully managed turn-around of financially insolvent organization including work with local banking institutions (to deal with defaults on a short term working capital line of credit) and with representatives for bondholders (defaults on a long term revenue bond financing).

Downsizing staffing issues.

Developed marketing strategies to stabilize operations.

1980-87 Partner, Memel, Jacobs, Pierno Gersh & Ellsworth, Los Angeles, California

Private practice of corporate financial law including tax exempt revenue bond issues, corporate restructurings and certificate of need determinations.

1975-1980Associate, Hahn, Loeser, Freedheim, Dean & Wellman, Cleveland, Ohio

Private practice of corporate financial law including certificate of need determinations, tax-exempt revenue bond issues, corporate restructurings and certificate of need determinations.

1972-1975 University of North Carolina School of Law

Coursework in law
North Carolina Law Review
Order of the Coif national honors society
Breckinridge Tax Prize (1975)
American Jurisprudence Awards (Torts, Civil Procedure, Administrative Law, Remedies)
Founding member, Parker International Law Society

1970-1972 Operations Sergeant, HQ Commandant, HQ XVIII Airborne Corps and Fort Bragg

Troop movement coordination
Coordination of parachute training for HQ company and developed operations plans

Scholarship

Foreman, S. (2010). A Different Corruption Paradigm, *Review of Business Research* (forthcoming June 2010).

Foreman, S., Kubyshkin, A., Ludan, V.Sukhareva, I. (2009)Trading Ideas: Health Care Management in the US and Ukraine. *Journal of Applied Business and Economics*, 10(1): 25.

Foreman, S., (2009). Health Care Reform in Crimea, *Crimea Izvestia (Verkovna Rada)*, 86(4289): 4-5 (May 16).

Foreman, S., Kubyshkin, (2009). A. Optimal Governmental and Private Roles in Health Care Financing. *International Journal of Strategic Management*, 9(1):75-82.

Foreman, S., Sukhareva, I. and Kubyshkin, (2008). A., A Comparison of Selection and Education of Healthcare Managers in Ukraine and the US. *Crimea Medical Journal* (Dec).

Foreman, S. and O'Roark, B. (2009). Home and Community Based Services: Lemonade or Hemlock. Currently under review Pennsylvania Economics Association Journal.

Foreman, S, Litzinger, P, O'Roark, B., & Flanegin, F. (2009). Aging: Another Contribution to the Theory and Empirics of Economic Growth. *International Journal of Business Research*, 8(1):

Foreman, S, Litzinger, P, O'Roark, B., & Flanegin, F. (2008). International Financial Implications of Aging, International Journal of Finance and Economics. *European Journal of Management.*

Foreman, S, Litzinger, P, O'Roark, B., & Flanegin, F. (2008). Financial Policy for an Aging World. *Proceedings, International Academy of Business and Economics*, Stockholm.

Foreman, S, Litzinger, P, O'Roark, B., & Flanegin, F. (2008). The Cost of Aging, International Competitive Advantage (Disadvantage). *American Society of Business and Social Sciences* 15(1): 430-443.

Foreman, S. (2008). *The State of Medicine.* Harrisburg, PA: Pennsylvania Medical Society.

Holstein, A. & Foreman, S. (2007). Cross-state outcomes and Medicaid generosity. Pennsylvania Economics Association Journal (2007).

Holstein, A. & Foreman, S. (2006). Medicaid spending and health outcomes. Proceedings: Pennsylvania Economics Association.

Foreman, S. (2006). *The State of Medicine.* Harrisburg, PA: Pennsylvania Medical Society.

Maioulis, G, & Foreman, S. (2004). The myth of the "bad doctors" Toward A New Theory of Risk of Failure in Medical Care . *Frontiers in Service Delivery.*

Foreman, SE, Emmons, D, Wasniak, G. (2001). Economic Consequences of Collective Bargaining by Physicians, *JAMA* 286: 1837-39.

Banks DA, Foreman SE, Keeler TE. (1999). Cross-subsidization in hospital care: some lessons from the law and economics of regulation. *Health Matrix* 9(1):1-35

Foreman, S.E., Shea, D.G., (1998). Information and Markets: On-Time Performance Reports, *Review of Industrial Organization*.

Sonnad, S.S. & Foreman, S.E. (1997). A physician incentive approach to implementation of medical practice guidelines. *Health Economics* 6, 467-77.

Foreman SE, Yu LC, Barley D, Chen LW. (1998) Use of health services by Chinese elderly in Beijing. *Medical Care* 36(8):1265-82.

Foreman, S.E. & Keeler, T.E. (1998). Regulation and deregulation. *The New Palgrave Dictionary of Economics and the Law*.

Zhang, A., Yu, L.C., Yuan, J., Tong, Z, Yang, C. & Foreman, S.E. (1997). Family and cultural correlates of depression among Chinese elderly. *International Journal of Social Psychology* 34(3), 199-212.

Foreman, S.E., Shea, D.G., & Kenkel, D. (1996). Information and the cost and quality of bypass surgery. *Journal of Cost and Quality, 2*, 23-29.

Foreman, S.E., Scheffler, R.M., Hu, T.W. & Feldstein, P.J. (1996). A multi-equation model of payments and public access to services: The case of dentistry. *Applied Economics* 28, 1359-68. (International Management Association Hall of Fame.)

Foreman, S.E., Wilson, J.A., & Scheffler, R.M. (1996). Monopoly, monopsony and contestability in health insurance: A Study of Blue Cross Plans, *Economic Inquiry* 34(4), 662-77.

Foreman, S.E. & Keeler, T.E. (1995). The economics of hospital cross subsidization. *University of California, Berkeley NBER Working Paper 95/236.*

Foreman, S.E., Shea, D.G., & Kenkel, D. (1995). Cost and quality information and health care market reform. *Advances in Health Economics and Health Services Research, 15*, 137-53.

Foreman, S.E. (1993). Box-Jenkins ARIMA analysis of airline safety data. *The Logistics and Transportation Review, 29*, 221-240.

Scheffler, R.M., Foreman, S.E., Cuffel, B. & Mackley, C. (1993). A Model Mental Health Benefit, Review and Critique. Accepted for publication by *Health Affairs* but not published.

Foreman SE, Roberts RD. (1991). The power of health care value-adding partnerships: meeting competition through cooperation. *Hosp Health Services Adm. Summer* 36(2):175-90. (1992 Edgar Hayhow Award). Reprinted in S. Levey (Ed.), Hospital Leadership and Accountability. Ann Arbor, MI.: Health Administration Press.

Scheffler, R.M., Foreman, S.E., Cuffel, B.J., & Mackley, C. (1994). Mental health benefits in the Clinton Plan. *Health Affairs II,* 201-210.

Exhibit B Materials Reviewed

In re: Aetna UCR Litigation, Second Joint Consolidated Amended Class Action Complaint;

AET-00000502;

AET-00000600;

AET-0000001;

AET-00296986;

AET-00913905;

AET-01163366;

AET-C 0000995;

Aetna materials including emails, AET-01059356 et seq.;

Franco, *et al.* v. Connecticut General Life Insurance Company, CIGNA Corp., *et al.* Consolidated Amended Class Action Complaint;

CIG00493123;

CIG000651356;

CIG000623420;

CIG015095197;

CIGNA claims data CIG 015095194, CIG 015095196, CIG 015095197, CIG 028888383, CIG 028897753, CIG 025061253, CIG 025061254, CIG 025061255, CIG 025479372, Extraction Logic, Lisa Wick Documents, data dictionaries for claim providers, Proclaim production, CIEB Diamond Data Dictionary;

ACAS Claim Data Production 2001-2009 including AET 00500964, AET 00500965, AET 00500966, AET 00500967 and AET 00297211;

Aetna Behavioral Health Internet Site: http://www.aetna.com/individuals-families-health-insurance/member-guidelines/outofnet_behealth.html (accessed April 2, 2010);

Health Care Report: The Consumer Reimbursement System is Code Blue, Office of the Attorney General, State of New York, Jan. 2009 ("NYAG Report");

Committee on Commerce, Science and Transportation, Office of Oversight and Investigations, Underpayments to Consumers by the Health Insurance Industry, Staff Report for Chairman Rockefeller, June 24, 2009 ("Rockefeller Report");

Expert Report in the Matters of Wachtel v. Health Net and McCoy v. Health Net, by Bernard R. Siskin, PhD, March 2004 ("Siskin 2004 Report");

Deposition of Carla Gee dated March 17, 2010;

Deposition of Carla Gee dated March 18, 2010;

Deposition of Wendy Larsen (Rough) dated June 29, 2010;

Deposition of Susan Seare dated July 13, 2010;

Deposition of Lisa Wick dated February 3, 2010;

Deposition of James Cross dated March, 23, 2010;

Deposition of Deborah Justo dated March 25, 2010;

Deposition of Hatzikostas (rough) dated March 26, 2010;

Deposition of Maureen Altier dated October 26, 2007;

Deposition of Wendy Sherry dated February 12, 2010;

State of New York, Office of the Attorney General, In the matter of Aetna, Inc., Assurance of Discontinuance Under Executive Law §63(15)(2009);

INGENIX01800147;

INGENIX01801276;

INGENIXMDL000004623;

INGENIXMDL000013812-13819;

INGENIXMDL000018489;

INGENIXMDL000105315;

INGENIXMDL000109228;

INGENIXMDL000185872;

INGENIXMDL000189345;

INGENIXMDL000202216;

INGENIXMDL000248741;

INGENIXMDL000257826;

INGENIXMDL000451135;

INGENIXMDL000456618;

INGENIXMDL000457826;

INGENIXMDL000527453;

INGENIXMDL000541071;

INGENIXMDL000542148;

INGENIXMDL000666852;

INGENIXMDL000696332;

INGENIXMDL000754244;

INGENIXMDL000754414;

INGENIXMDL000754736;

INGENIXMDL000756673;

INGENIXMDL000778017;

INGENIXMDL000929773;

INGENIXMDL000950390;

INGENIXMDL001120029

Data Appendix 1

Comparison of 80th Percentile Values
With and Without High-low screen
90 Most Common CPT / Geozip Combinations
CIGNA PPO Data

		2000			2001			2002			2003		
CPT	GEOZIP	NO SCR	SCR	DIFF	NO SCR	SCR	DIFF	NO SCR	SCR	DIFF	NO SCR	SCR	DIFF
90806	70	240	200	40	160	150	10	150	150	0	150	150	0
90806	100	300	280	20	270	175	95	165	175	-10	175	160	15
90806	117	200	180	20	165	150	15	140	140	0	150	150	0
90806	600	180	150	30	170	125	45	125	125	0	130	125	5
90806	601	125	120	5	125	120	5	120	120	0	120	120	0
90806	606	240	190	50	200	150	50	150	155	-5	150	140	10
90806	627	110	105	5	100	100	0	100	95	5	125	100	25
90806	850	125	125	0	125	125	0	125	125	0	125	125	0
90806	852	130	125	5	125	120	5	125	125	0	125	125	0
90806	926	150	150	0	150	145	5	150	145	5	150	150	0
97110	70	100	74	26	100	60	40	60	60	0	110	60	50
97110	100	95	80	15	100	80	20	75	75	0	100	80	20
97110	117	110	82	28	100	80	20	75	75	0	82	80	2
97110	600	114	107	7	110	96	14	94	100	-6	116	100	16
97110	601	126	109	17	150	120	30	120	120	0	120	120	0
97110	606	114	100	14	133	120	13	124	120	4	150	130	20
97110	627	120	120	0	94.5	90	4.5	94.5	84	10.5	105	105	0
97110	850	118	106	12	120	105	15	101	105	-4	102	90	12
97110	852	105	98	7	105	100	5	80	100	-20	80	72	8
97110	926	70	55	15	70	55	15	50	50	0	60	49	11
97140	70	70	65	5	70	65	5	65	65	0	65	65	0
97140	100	85	85	0	80	75	5	75	75	0	80	75	5
97140	117	70	60	10	67	60	7	60	60	0	60	60	0
97140	600	78	60	18	80	65	15	70	70	0	70	62	8
97140	601	70	55	15	90	60	30	60	60	0	65	60	5
97140	606	75	65	10	82	65	17	62	61.6	0.4	75	62	13
97140	627	57	55	2	45	45	0	41	41	0	40	40	0
97140	850	50	45	5	50	45	5	50	47.85	2.15	70	50	20
97140	852	48	45	3	48	45	3	45	45	0	60	45	15
97140	926	65	55	10	65	55	10	52	52	0	70	55	15
97530	70	72	72	0	72	72	0	72	72	0	72	72	0
97530	100	75	65	10	65	65	0	65	65	0	72	66	6
97530	117	60	60	0	50	50	0	50	45	5	60	50	10
97530	600	130	125	5	152	130	22	150	150	0	140	138	2
97530	601	105	105	0	118.5	110	8.5	125.5	109.5	16	130	130	0
97530	606	128	128	0	125	110	15	125	125	0	130	125	5
97530	627	90	49	41	49	49	0	49	49	0	40	49	-9
97530	850	90	90	0	120	90	30	67.5	70	-2.5	76	50	26
97530	852	130	90	40	80	60	20	45	45	0	60	45	15
97530	926	74	72	2	77	74	3	60	60	0	68	58	10
98941	70	60	60	0	60	60	0	60	60	0	60	60	0
98941	100	75	75	0	78	75	3	80	75	5	85	80	5
98941	117	65	65	0	65	65	0	65	65	0	70	70	0
98941	600	50	48	2	50	50	0	50	50	0	55	55	0
98941	601	50	49	1	50	50	0	50	50	0	50	50	0
98941	606	55	53	2	55	52	3	55	55	0	57.6	55	2.6
98941	627	52	52	0	52	52	0	45	45	0	48	45	3
98941	850	60	60	0	60	60	0	60	60	0	60	60	0
98941	852	57	56	1	59	59	0	60	60	0	60	60	0
98941	926	60	60	0	65	65	0	70	70	0	70	70	0
99212	70	67	65	2	70	70	0	75	70	5	75	75	0

99212	100	100	100	0	100	100	0	100	100	0	120	105	15
99212	117	70	70	0	75	70	5	70	70	0	75	75	0
99212	600	60	60	0	65	64	1	65	65	0	66	65	1
99212	601	55	53	2	60	60	0	61	60	1	66	65	1
99212	606	60	60	0	63	62	1	65	65	0	70	68	2
99212	627	51	51	0	54	54	0	55	55	0	55	57	-2
99212	850	50	50	0	58	58	0	61	61	0	63	62	1
99212	852	49	49	0	51	50	1	51	52	-1	56	55	1
99212	926	60	60	0	61	60	1	65	60	5	65	65	0
99213	70	75	75	0	80	80	0	85	80	5	85	85	0
99213	100	125	125	0	130	125	5	135	130	5	150	150	0
99213	117	80	75	5	85	75	10	80	80	0	90	85	5
99213	600	74	70	4	76	75	1	80	80	0	87	85	2
99213	601	70	70	0	76	75	1	80	80	0	84	80	4
99213	606	75	75	0	82	82	0	87	87	0	95	93	2
99213	627	66	66	0	70	70	0	71	71	0	72	72	0
99213	850	66.5	65	1.5	75	70	5	75	75	0	86	78	8
99213	852	62	61	1	70	66	4	70	70	0	75	74	1
99213	926	75	72	3	75	75	0	80	75	5	85	85	0
99214	70	100	100	0	107	100	7	105	100	5	120	105	15
99214	100	175	175	0	175	175	0	190	180	10	200	200	0
99214	117	110	100	10	120	105	15	110	105	5	125	115	10
99214	600	105	105	0	115	110	5	116	116	0	126	125	1
99214	601	99	96	3	110	105	5	113	111	2	125	120	5
99214	606	110	110	0	128	125	3	135	132	3	136	135	1
99214	627	99	99	0	105	105	0	105	105	0	110	110	0
99214	850	100	95	5	114	100	14	105	105	0	134	112	22
99214	852	90	90	0	100	98	2	105	100	5	115	110	5
99214	926	102	100	2	110	100	10	105	100	5	125	107	18
99215	70	160	150	10	175	170	5	175	175	0	190	175	15
99215	100	225	210	15	250	225	25	250	240	10	275	250	25
99215	117	150	150	0	165	150	15	160	150	10	175	165	10
99215	600	170	170	0	180	175	5	185	180	5	200	190	10
99215	601	153	150	3	164	159	5	170	170	0	185	185	0
99215	606	170	170	0	185	185	0	200	200	0	201	200	1
99215	627	150	150	0	175	175	0	175	175	0	168	168	0
99215	850	146	142	4	170	150	20	158	158	0	215	160	55
99215	852	150	150	0	156	150	6	155	150	5	172	162	10
99215	926	170	160	10	175	160	15	163	160	3	188	170	18
		102.25	95.82	6.42	103.41	94.52	8.88	96.65	95.555	1.095	104.98	98.18	6.81
PCT DIFF			6.29			8.6			1.13			6.5	

		2004			2005			2006			2007			2008		
CPT	GEO	NO SCR	SCR	DIFF	NO SCR	SCR	DIFF	NO SCR	SCR	DIFF	NO SCR	SCR	DIFF	NO SC	SCR	DIFF
90806	70	160	155	5	160	160	0	165	165	0	175	175	0	175	175	0
90806	100	175	160	15	175	175	0	185	175	10	200	190	10	200	200	0
90806	117	150	150	0	150	150	0	150	150	0	150	150	0	155	150	5
90806	600	130	130	0	135	130	5	140	135	5	140	140	0	150	144.5	5.5
90806	601	125	125	0	136	135	1	140	140	0	140	140	0	150	150	0
90806	606	144	140	4	150	150	0	150	150	0	150	150	0	150	150	0
90806	627	125	105	20	140	125	15	130	130	0	130	130	0	130	130	0
90806	850	140	125	15	130	130	0	140	130	10	150	140	10	140	135	5
90806	852	125	125	0	130	125	5	135	125	10	145	135	10	135	130	5
90806	926	150	150	0	150	150	0	155	150	5	160	152.5	7.5	160	150	10
97110	70	100	60	40	93.39	65	28	110	70	40	120	70	50	120	70	50
97110	100	100	80	20	100	85	15	132.36	90	42	150	90	60	150	95	55
97110	117	90	84	6	90	85	5	100	90	10	100	84	16	117	84	33
97110	600	120	104	16	159	124	35	164	140	24	180	180	0	195	192	3
97110	601	132	130	2	136	132	4	144	130	14	150	140	10	150	150	0
97110	606	180	150	30	180	165	15	180	180	0	204	200	4	240	240	0
97110	627	105	105	0	126	126	0	150	142	8	212	200	12	200	200	0
97110	850	120	95	25	120	120	0	135	135	0	136	135	1	156	156	0
97110	852	90	72	18	108	80	28	108	100	8	110	100	10	135	105	30
97110	926	60	50	10	88	50	38	90	50	40	90	55	35	96	55	41
97140	70	70	65	5	70	65	5	75	70	5	75	75	0	75	75	0
97140	100	80	75	5	100	80	20	110	80	30	140	85	55	160	90	70
97140	117	60	60	0	75	60	15	75	65	10	80	70	10	75	70	5
97140	600	80	60	20	80	60	20	85	63	22	90	65	25	90	65	25
97140	601	65	60	5	70	60	10	72	64	8	75	58.28	16.7	70	58	12
97140	606	82	65	17	90	64	26	75	65	10	90	65	25	116	68	48
97140	627	46.25	45	1.2	48	46.25	1.75	52	48	4	52	52	0	60	55	5
97140	850	72	50	22	70	50	20	100	50	50	100	50	50	100	50	50
97140	852	60	50	10	90	50	40	90	50	40	90	50	40	94	50	44
97140	926	80	55	25	90	55	35	100	55	45	100	55	45	110	55	55
97530	70	75	74	1	75	75	0	85	75	10	80	75	5	80	75	5
97530	100	70	66	4	87	80	7	90	85	5	90	90	0	90	90	0
97530	117	65	50	15	82.5	60	22.5	82.5	65	17.5	82.5	74.06	8.4	84	82.5	1.5
97530	600	145	145	0	145	145	0	150	150	0	160	160	0	160	160	0
97530	601	120	120	0	120	100	20	140	92	48	140	91.32	48.6	140	70	70
97530	606	152	152	0	150	150	0	168	160	8	168	168	0	168	168	0
97530	627	25	49	-24	100	49	51	144	144	0	48	48	0	70.44	70.44	0
97530	850	90	50	40	152	50	102	110	50	60	103.5	50	53.5	106	50	56
97530	852	68	45	23	90	50	40	100	55	45	84	60	24	140	52	88
97530	926	70	58	12	88	55	33	70	55	15	90	55	35	90	55	35
98941	70	65	65	0	65	65	0	65	65	0	70	70	0	70	70	0
98941	100	88	85	3	95	95	0	100	97	3	100	100	0	100	100	0
98941	117	72	72	0	75	75	0	75	75	0	80	79	1	80	80	0
98941	600	60	57	3	60	60	0	60	60	0	60	60	0	60	60	0
98941	601	50	50	0	53	53	0	53	53	0	55	55	0	56	55	1
98941	606	60	60	0	60	60	0	60	60	0	65	60	5	60	60	0
98941	627	50	48	2	53	50	3	60	50	10	58	50	8	58	50	8
98941	850	60	60	0	65	65	0	68	68	0	66	66	0	68	68	0
98941	852	60	60	0	60	60	0	60	60	0	61	60	1	65	62	3
98941	926	68	68	0	75	75	0	73.8	73.8	0	75	75	0	80	75	5
99212	70	75	73	2	75	75	0	78	75	3	80	75	5	85	80	5
99212	100	125	115	10	135	125	10	150	135	15	150	150	0	165	150	15
99212	117	80	80	0	80	80	0	85	80	5	85	80	5	95	80.05	14.9
99212	600	69	68.5	0.5	74	74	0	75.9	75	0.9	75	75	0	81	80	1
99212	601	68	67	1	70	70	0	73	72	1	75	75	0	81	75	6
99212	606	75	75	0	78	78	0	82	81	1	87	86	1	91	90	1
99212	627	57	60	-3	58	59	-1	63	62.76	0.24	64	64	0	66	66	0
99212	850	68	65	3	68	65	3	71	65	6	71.04	65	6.04	71.04	65	6.04
99212	852	60	55	5	61	60	1	65.95	61	4.95	73.4	65	8.4	75	67.95	7.05
99212	926	65	65	0	67	65	2	70	65	5	70	65	5	73	68	5
99213	70	95	85	10	100	90	10	100	95	5	100	100	0	105	100	5
99213	100	150	150	0	160	155	5	175	155	20	188	175	13	200	180	20
99213	117	100	85	15	100	90	10	109	90	19	124	95	29	125	100	25

99213	600	90	90	0	95	92	3	100	100	0	105	105	0	110	110	0
99213	601	88	85	3	90	90	0	99	96	3	102	100	2	105	104	1
99213	606	100	99	1	104	102	2	110	108	2	114	111	3	120	114	6
99213	627	76	74.49	1.5	79.5	76.86	2.64	82	82	0	89	88	1	90	90	0
99213	850	85	78	7	90	80	10	95	85	10	97.5	90	7.5	100	90	10
99213	852	78	75	3	85	78	7	90	80	10	100	90	10	100	95	5
99213	926	90	85	5	90	90	0	95	90	5	100	95	5	109	100	9
99214	70	125	105	20	130	105	25	140	110	30	150	120	30	150	139	11
99214	100	210	200	10	220	220	0	225	220	5	250	235	15	260	250	10
99214	117	135	117	18	145	120	25	150	125	25	160	135	25	180	146	34
99214	600	136	135	1	145	141.1	3.89	154	150	4	165	160	5	170	168	2
99214	601	133	129	4	143	140	3	150	150	0	160	155	5	165	160	5
99214	606	145	144	1	152	150	2	155	152	3	171.15	160	11.1	180	175	5
99214	627	110	108.9	1.0	110	110	0	122	122	0	126	126	0	131	130	1
99214	850	147	120	27	141.32	125	16.3	139	128	11	150	139	11	161	144	17
99214	852	120	117	3	125	120	5	135	125	10	153	140	13	165	148	17
99214	926	130	120	10	135	130	5	144	139	5	150	140	10	152	150	2
99215	70	200	181	19	200	195	5	200	200	0	200	190	10	200	189	11
99215	100	300	283	17	310	300	10	350	325	25	355	350	5	355	350	5
99215	117	185	175	10	200	165	35	220	165	55	225	175	50	250	175	75
99215	600	209.61	200	9.6	210	209.6	0.39	245	232	13	250	240	10	273	262	11
99215	601	189	186	3	210	207	3	225	225	0	230	230	0	238	238	0
99215	606	225	221	4	230	230	0	245	245	0	252	250	2	271	250.9	20.0
99215	627	168	168	0	168	168	0	196	196	0	210	210	0	210	210	0
99215	850	222	175	47	225	200	25	240	206	34	240	235	5	255	250	5
99215	852	181	174	7	195	176	19	200	200	0	222	200	22	230	221	9
99215	926	200	175	25	200	185	15	225	200	25	225	200	25	225	205	20
		109.93	101.9	7.9	117.15	106.8	10.3	124.23	112.7	11.4	129.05	117.4	11.6	134.97	121.29	13.6
PCTDIF			-7.2			-8.8			-9.2			-9.0			-10.1	

Data Appendix 2

80th percentile values by month nationally
Ingenix contributor data -100 most common CPT codes
January 2006-December 2008

Cpt/month	1	2	3	4	5	6	7	8
17000	115	115	115	115	116	117	118	118
20610	195	195.63	197	198	199	200	200	200
36415	19	19	19.5	19	20	20	20	19.8
71010	117	125	125	125	125	105	102	110
71020	125	128.66	128	127.5	127	123.1422	125	122
76499	880	886.5176	884.75	886	894.67	904	915.508	966.3197
80048	65	65	65	65	65	61.6	63	60.95
80050	188.45	188.45	189	189	189	190	190.6	190.6
80053	67.27	68	68	68.14	68.14	66	67	66
80061	99.5	100	100	100	100	100	100.75	100.75
80076	55.75	55.75	55.75	55.75	55.75	55.75	56	55.15
81000	22	22	22	22	22	22	22	22
81001	39	39	39	39	39	39	39	39
81002	18	18	18	18	18	18	18	18
81003	29	30.9	30.9	31	30.9	30	30	30
83036	70	70	70	70.4	70	70	70.4	70.4
84153	112	112	112	112.12	112.33	112	114	114.35
84439	116.15	116.15	116.15	116.15	116.15	116.15	116.15	116.15
84443	108	108	108	108	108	108	108	108
85025	42.25	43	42.75	43	42.33	42	42	42
85027	40	41	41	41	41	40	41	40
85610	33.1	34	33.1	33	33	33	33	33
87086	62	62	62	62	60.5	60.5	60	60
87880	41	41.74	41.2	41	42	42.2	43	42.5
88142	81.15	82	81.15	81.15	81.15	81.15	81.15	82
88175	94	94	95	98.52	101	101.81	104.75	104.75
88305	200	200	203	203	200	200	200	202
89240	99.5	99.75	100.03	99.75	100.05	100	101.62	102.45
90471	30	30	31	31	31	31	31	30
90472	23	23	23	23	23	24	24	24
90658	25	28	30	32	40	35	30	30
90772	40	40	41	41	41	42	43	43
90806	150	150	150	150	150	150	150	150
92012	100	100	102.98	103	105	105	105	105
92014	139	140	140	140	140	140	140	141
92015	40	42	43	43	43	44	43	45
93000	85	85	85	85	85	85	85	85
93010	48	48	48	48	48	48.55	49	49
93307	557	560	560	558	559	557	558	558
93320	325	325	325	325	325	325	325	325
93325	301	305	305	303	305	305	305	305
95117	37	37	37	37	37	38	38	37
97001	145	145	146.5	149	150	150	149.56	150
97010	30	30	30	30	30	30	30	30

97012	35	36	36	36	36	37	37	37
97014	35	35	35	35	35	35	35	35
97032	45	45	45	45	45	45	45	45
97035	40	40	40	40	40	40	40	40
97110	60	60	60	60	60	60	60	60
97112	55	55	55	55	55	55	55	55
97140	58	58	58	59	59	60	60	60
97530	60	60	60	60	60	60	60	60
98940	50	50	50	50	50	50	50	50
98941	60	60	60	60	60	60	60	60
98942	75	75	75	75	75	75	75	75
98943	50	50	50	50	50	50	50	50
99000	23	23	23	23	24	24	25	25
99202	115	115	116	117	117	119	120	120
99203	167	167.36	170	170	172	172	173.33	175
99204	238	240	240	244	245	247.61	249	250
99211	50	50	50	50	50	50	50	50
99212	72	73	74	74	75	75	75	75
99213	95	95	95	95	97	97.7	99	98.6
99214	148	148	150	150	150	150	150	150
99215	219	220	220	221	225	225	225	225
99231	90	91.25	92	93	93	94	94	95
99232	127.72	130	130	130	131	132	132	134
99233	196	200	200	200	200	200	200	200
99243	250	250	250	250	250	251	253	252
99244	337	340	340	340	342	344	347	346
99283	254	256	259	259	260	262	263	260
99284	383	385	386	392	394	390	397	394
99285	576	581	584	589	590.32	588	590.32	586
99391	131	132	132.8256	132	134	135	135	135
99392	145	146	147	147	148	149	149	148
99395	180	180	185	185	185	185	188	187.4
99396	198	199	200	200	200	200	200	200
D0120	41	42	42	42	42	42	42.14	43
D0140	67	67	68	68	69	69	69	70
D0150	70	70	71.1361	72	72.5	73	74	73
D0210	120	120	120	120	120	120	120	120
D0220	25	25	25	25	25	25	25	25
D0230	20	20	20	20	21	21	21	21
D0272	37	38	38	38	38	38	38	38
D0274	55	55	55	55	56	56	56	56
D0330	95	95	95	95	95	95	95	96
D1110	80	80	81	81	82	82	82	82
D1120	58	58	59	59	59	59	59	60
D1203	34	34	33	35	35	35	35	37
D1204	30	31	31	31	31	31	31	32
D1351	48	48	48	48	48	48	48	49
D2140	125	125	126	126	128	128.33	130	132
D2150	152	154	155	154	155	155	157	160
D2391	149	150	150	150	150	150	150	150

D2392	193	194	195	195	195	195	195	196
D4341	225	225	225	225	225	228	228	228
D4910	126	127	128	128	129	130	129	129
D7140	130	130	132	132	135	135	135	137
G0283	38	39	39	38.5	38.5	39	38	39
Average	118.6347	119.4056	119.8356	120.0907	120.6595	120.6009	121.0735	121.7088
cpt	9	10	11	12	13	14	15	16
17000	120	118	120	120	120	120	120	120
20610	200	200	200	200	200	200	201	201.3
36415	20	20	20	20	20	20	20	20
71010	143.8002	123.09	115	122.38	116	133	126	137
71020	125	123	125	125	127	150	130	134
76499	921.5	949	948	940.5869	975	679.88	997	952
80048	65	63	63	64	65	69	65	66.4
80050	189.8	190.6	190.6	190.6	192	188.45	192.3379	192.25
80053	70.44	67.71	68.14	68.36	69	73.7	69.2	70.42
80061	94	100.75	100.75	100.75	95	96	93.37	94.67
80076	58.7	55.8	55.75	55.75	57	59	57	59
81000	23	22	22	23	23	23	23	23
81001	39	39	39	39	39	39.69	39	39.2
81002	19	19	19	19	19	19	19	19
81003	29.25	30	30	31	31	30	31	31
83036	69.3	70.31	70.31	70.31	70.8	69.3	70.8	71
84153	114.35	114.35	114.35	114.35	114.35	112	114.4	114.4
84439	116.15	116.15	116.15	116.15	116.15	116.15	116.15	116.15
84443	108	108	108	108	108	108	108	108
85025	42.25	42	42	42	43	45	43.25	44
85027	42	40	40.2	41	42	44	42	42.44
85610	33.5	33.1	33.6	33.6	35	35	35	35
87086	60.5	61.75	62.64	64	64	64	64	64
87880	42	43	42	42.2	43	44	43	43
88142	85	81.15	81.15	81.16	90	80	90	90.36
88175	95	104.75	102.25	102.25	113.62	97.09	112	111.25
88305	210	205	203	207	210	214.5	210	211
89240	101.33	103	103.28	103.89	106.1281	86.036	106	106.83
90471	30	28	29	29	30	30	30	30
90472	24	25	25	25	25	25	25	25
90658	30	28	27	29	30	25.24	30	30
90772	42	41	41	41	43	44	44	44
90806	150	150	150	150	150	150	150	150
92012	105	105	105	105	109	110	110	109
92014	141	140	145	145	150	148	149	146
92015	45	45	45	45	47	45	50	50
93000	85	85	85	85	85	85	85	85
93010	50	50	50	50	50	50	50	50
93307	565	560	560	560	565	573	565	565
93320	325	325	325	325	325	335	325	328
93325	307.53	308	310	310	313	313.77	313	313
95117	38	38	38	38	38	39	38	38
97001	146	150	150	150	150	150	150	150

97010	30	30	30	30	31	32	32	33
97012	37	38	38	38	39	38	40	40
97014	35	35	35.95	36	36	36	36	36
97032	45	45	45	45	45	45	45	45
97035	40	40	40	40	40	40.5	41	41
97110	60	60	60	60	60	60	60	60
97112	55	55	55	55	55	55	56	58
97140	59	60	60	60	60	60	60	60
97530	60	60	60	60	60	60	60	60
98940	50	50	50	50	50	50	50	50
98941	60.95	60	60	60	62	60	62	61
98942	75	75	75	75	75	75	75	75
98943	50	50	50	50	50	50	50	50
99000	23	25	25	25	25	25	25	25
99202	121	120	120	120	122	122.4	123	123
99203	175	175	175	175	175	176	178	179
99204	250	250	250	250	250	250	250	251
99211	50	50	50	50	50	51	50	50
99212	75	75	75	75	75	75.81	76	76
99213	99	99	100	100	100	100	100	100
99214	150	150	150	150	155	156	156	156
99215	225	225	225	226	231.72	234	234	234
99231	96	95	95	96	98.23	100	98.16	97
99232	135	134	135	135	138	139	139.26	140
99233	200	200	200	200	201	201	201	201
99243	252	254	254	255	259	261	260	260
99244	346	350	350	350	350	354	353.28	353
99283	275	267	267	269	280	287	282	289
99284	414.042	405	405	407	425	440	437	443
99285	591	601	601	607	631	643	643	650
99391	138	135	136	136	138	140	140	140
99392	150	150	150	150	150	150	150	150
99395	190	189	190	190	190	190	193	191
99396	202	200	202	204	207	207	208	208
D0120	42	43	43	44	45	43	43	43
D0140	68	70	70	70	70	70	70	69
D0150	72	75	75	75	75	75	75	75
D0210	120	121	122	123	123	122	123	122
D0220	25	25	25	25	25	25	25	25
D0230	21	21	21	21	21	21	21	21
D0272	38	38	39	39	39	38	39	38
D0274	56	56	57	57	57	56	57	56
D0330	95	96	97	98	97	95	96	95
D1110	82	83	83	84	85	82	83	82
D1120	60	60	60	60	60	60	60	60
D1203	58	35	35	35	33	32	33	33
D1204	31	31.4	32	32	32	32	32	32
D1351	48	48	49	49	50	48	49	48
D2140	120	130	130	133	142	128.1	130	130
D2150	148	160	160	160	175	160	158	160

D2391	150	150	151.5943	154	155	153	153	155
D2392	195	197	198	200	200	199	200	200
D4341	225	230	230	234	234	230.2	235	232
D4910	128	130	130	130	132	131	131	131
D7140	135	138	138	140	136	130	131	132
G0283	40	40	39	39	38	41	36	36
Average	122.1454	122.2819	122.4113	122.862	124.7677	121.9577	125.2041	125.1482
cpt	17	18	19	20	21	22	23	24
17000	120	120	120	120	121	120	121.9	122
20610	203	205	205	206	207	204	207	206
36415	20	20	20	20	20	20	20	20
71010	150	150.15	156	160	160	155	155	146.72
71020	136	140	140.05	142.5	145	141	140	138
76499	960	903.7	823	829	906.5	918.206	912.89	899
80048	67	67.7	67.7	67.7	69	69	67.8	69
80050	191.85	192.25	191.2	191.6	191.25	191.6	191.95	191.97
80053	70	71	70	70	71	70	69	70
80061	94.66	95	95	95	95	95	96	95.8
80076	58.1	59	59	58.8	58.5	58.4	58	59
81000	23	23	23	23	23	23	23	23
81001	39.43	39.29	39.43	39	39.75	39.75	39.2	39
81002	20	20	20	20	20	20	20	20
81003	31	31	31	31	31	31	31	31
83036	71	71	70.75	70.75	70.8	71	71	71
84153	114.35	112	112	112	112	112	112	112
84439	116.15	116.15	116.15	116.15	116.15	116.15	116.15	116.15
84443	108	108	108	108	108	108	108	108
85025	44	44	44	44	44	44	44	44
85027	42.33	43	42	42	42	42.75	42.75	43
85610	35	35	35	35	35	35	35	35
87086	64	64	64	64	64	64	64	64
87880	44	44	45	45	45	45	45	45
88142	90	90	90	90	90	90	90	90
88175	110	110	102.25	102.25	102.25	102.25	102.25	102.25
88305	210	210	211	211	211	214.75	212	215
89240	107	107.67	108.83	109.4	87	90	90	90
90471	30	30	30	30	31	30	30	31
90472	25	25	25	25	25	25	25	25
90658	30	30	30	30	30	30	30	30
90772	44	45	45	44	44	43	43	44
90806	150	150	150	150	150	150	150	150
92012	110	110	110	110	110	110	110	110
92014	150	150	150	150	150	150	150	150
92015	50	50	50	50	50	50	50	50
93000	85	85	85	85	85	85	85	85
93010	50	50	50	50	50	50	50	50
93307	565	565	571.34	575	567.66	570	571.17	575
93320	325	326.85	330	331	330	330	330	330
93325	313	313	315	316	314	315	317	317
95117	39	39	39	39	39	39	39	40

97001	150	150	150	150	150	150	150	150
97010	33	33	33.63	33	32	32	32	32
97012	40	40	40	40	40	40	40	40
97014	36	37	37	37	37	37	38	38
97032	45	45	45	45	45	45	45	45
97035	41	41	41	41	42	42	42	42
97110	60	60	60	60	60	60	60	60
97112	58	58	58	59	60	60	60	60
97140	60	60	60	60	60	60	60	60
97530	60	60	60	60	60	60	60	60
98940	50	50	50	50	51	51	51	51
98941	62	62	62	62	63	63	64	65
98942	75	75	75	75	75	75	75	75
98943	50	50	50	50	50	50	50	50
99000	25	25	25	25	25	25	25	25
99202	124	124	125	125	125	125	125	125
99203	180	180	180	182	182	183	184	184
99204	253	255	257	260	260	260	261	261.76
99211	50	51	51	51	51	50	50.5	51
99212	76.25	77.25	78	78	78	78	79	79
99213	102	102.47	104	104	105	104	105	105
99214	160	160	161	161	162	161	164	164
99215	236	238	239	239	240	240	242	244
99231	99	100	100	100	100	100	100	100
99232	140	143	144	144	144	145	145	145
99233	202	205	209	209	206.67	209	209	209
99243	260	265	265	265	265	265	267	268.3
99244	355	357	359	359	360	360	363	365
99283	294	294	294	295	295	298	296	300
99284	447	447	451	450	452	454	452	454
99285	648	650	654	654	654	657	654	660
99391	140	140	141	140.74	142	141	143	144
99392	151	151	153	152	155	155	155	155
99395	194	194	195	195	199	196.36	200	200
99396	208	208	210	210	210	210	210	211
D0120	43	44	44	45	46	46	46	47
D0140	70	70	71	75	75	75	75	75
D0150	75	75	75	76	76	77	78	80
D0210	124	125	125	125	125	125	127	129
D0220	25	25	26	26	26	26	26	27
D0230	21	21	21	22	22	22	22	22
D0272	39	39	39	40	40	40	40	40
D0274	57	58	58	59	60	60	60	60
D0330	97	97	98	100	100	100	100	101
D1110	84	84	84	85	88	88	89	89
D1120	62	61	61	64	65	64	65	65
D1203	33	33	33	34	35	35	35	35
D1204	32	32	32	33	33	33	34	34
D1351	49	49	49	50	50	50	51	52
D2140	130	132	130	140	150	150	150	152

D2150	160	161	160	165	181	182	185	188
D2391	155	155	155	159	160	160	161	164
D2392	200	200	200	204	205	205	208	210
D4341	236	239	240	242	242	244	246	250
D4910	133	134	135	135	135	135	135	136
D7140	135	135	137	142	145	145	149	150
G0283	37	37	38	37	38	39	39.55	40
Average	125.9305	125.8028	125.4276	126.1302	127.2074	127.3759	127.7082	128.05
cpt	25	26	27	28	29	30	31	32
17000	125	125	125	125	125	125	125	125
20610	210	206	208	205	210	206	210	210
36415	20	20	20	20	20	20	20	20
71010	151	154	156	160	169	183	194	207
71020	142	143	145	145	146.58	146	146.58	146
76499	914	1040.72	1088	1118	1137	1144	1124	1163
80048	69.25	69.9	69.9	69.9	69	69	67.25	67
80050	192.24	192.75	192.25	192.75	192.75	192.75	192.75	192.75
80053	72.3	72.31	72.31	73	72.31	73	73	72.31
80061	95.88	96.33	96.25	98	97	96.5	97.5	97.5
80076	60	59	60	60	59.03	60	60	60
81000	23	23	24	24	24	24	24	24
81001	39	39.2	39.75	39.75	39.75	39.5	39	39
81002	20	20	20	20	20	20	20	20
81003	31	31	31	31	31	31	31	31
83036	71.75	71.75	73	74	73.64	73.66	74	74
84153	112	112	112	112	112	112	112	112
84439	116.85	116.9	116.9	116.9	116.9	117	117	117
84443	108	108	108	108.1	108.05	108	108.1	108.1
85025	44.67	44.67	45	45	45	45	45	45
85027	43	43	42.75	43	43	43	43	43
85610	35	36	36	36.07	36.04	36	36.04	36.78
87086	64	64	64	64	64	64	64	64
87880	45	45	45	45	45	45	45	45
88142	90	90.36	90.36	92	91.45	91.46	91.46	92
88175	102.25	102.25	102.25	102.25	102.25	102.25	102.25	102.25
88305	224	225	224	223.5	225	225	225	225
89240	90	98	98	98.13	98.25	99.0563	101.2	100
90471	33	33	34	34	35	35	35	35
90472	25	25	25	25	25	25	25	25
90658	30	30	30	32	30	30	30	35
90772	44	43	44	44	44	44	45	45
90806	150	150	150	150	150	150	150	150
92012	111	115	115	113	115	115	115	115
92014	150	153	152	150	155	155	155	155
92015	50	54	55	55	55	55	55	57
93000	85	85	85	85	85	85	85	85
93010	50	50	50	50	50	50	50	50
93307	576	579	579	579	578.6	579	579	579
93320	336	336	334	334	334	334	337	337
93325	320	320	320	320	320	320	324	323

95117	40	40	40	40	40	40	40	40
97001	151	152	152.26	153	154	155	157	156
97010	32.94	33	35	35	35	35	35	35
97012	40	40	40	40	40	40	40	40
97014	38	38	38	38	38	39	39	38
97032	45	45	45	45	45	45	45	45
97035	42	42	42	42	42	42	43	43
97110	61	61.98	62	63	62.5	63	63	62
97112	60	60	60	60	60	60	60	60
97140	60	60	60	61	60.75	61	61	61.11
97530	60	61	62	62	61	61	61	61
98940	52.53	53	53	53	54	54.5	55	53
98941	65	65	65	65	65	65	65	65
98942	75	75	75	75	76	76	76	75
98943	50	50	50	50	50	50	50	50
99000	25	25	25	25	25	25	25	25
99202	125	125	126	126	126	126.5	127	128
99203	185	185	185	186	187	186	188	189
99204	264	265	266	267	270	270	271	271
99211	54	55	55	55	55	55	55	55
99212	80	80	80	80	80	80	80	80
99213	107	107	108	108	110	110	110	110
99214	166	166	167	167	169.9	170	172	172
99215	247	247	250	248	250	250	250	250
99231	100	100	100	100	103	102.456	103	103
99232	148	148	149	149	150	150	150	150
99233	210	210	211	211	214	217	220	220
99243	272	275	275	275	275	275	276	276.1
99244	370	372	375	373	375	375	380	380
99283	310	313	316.75	322	320	321	324	324
99284	460	460	467	475	474.95	476	479	483
99285	672	675	677	685	678	685	694	690
99391	144	145	145	145	145	145	145	146
99392	156	156	157	155	157	158	157	156
99395	200	200	200	200	200	200	200	200
99396	213	215	215	213	218	216.36	216.26	218
D0120	46	46	46.36	46	47	47	47	47
D0140	75	75	75	75	75	75	75	75
D0150	78	78	79	79	80	80	80	80
D0210	128	129	130	130	130	130	130	130
D0220	26.67	27	27	27	27	27	27	28
D0230	23	23	23.75	24	24	24	24	25
D0272	40	40.67	41	41	41	41	41	42
D0274	60	60	60	60	60	60	60	60
D0330	102	103	103	104	105	105	105	105
D1110	88	88	88.9	88.25	89	89	89	89.33
D1120	65	65	65	65	66	65	65	66
D1203	35	35	35	35	35	35	35	35
D1204	34	35	35	35	35	35	35	35
D1351	50	51	51	52	52	51	52	52

D2140	142	143	143	142	144	145	143	144
D2150	171.5	174	175	174	175	175	175	175
D2391	164	165	165	165	165	165	166	167
D2392	210	210	211	211	213	214	215	215
D4341	247	248	249	250	250	250	250	250
D4910	136.9763	138	138.5	138.4	139	139	140	139
D7140	150	150	150	150	150	150	150	150
G0283	40	40	40	40	40	40	40	40
Average	128.9273	130.7656	131.6994	132.2323	132.9061	133.2322	133.6302	134.2346
cpt	33	34	35	36				
17000	126	125	126	126				
20610	210	210	211	210				
36415	20	20	20	20				
71010	206	206	209	207				
71020	143	141	142	139				
76499	1200	1141	1124.978	1094.466				
80048	65	65	65	65				
80050	192.75	194	194	194.44				
80053	72	72.31	72.31	72				
80061	96	99	99.5	100				
80076	60	59	60	60				
81000	24	24	24	24				
81001	39	39	39.75	39				
81002	20	20	20	20				
81003	31	31	31	31				
83036	73.66	74	74	74				
84153	112	112	112	112				
84439	116.96	117	117.04	116.9				
84443	108.1	108.25	108.1	108.25				
85025	45	45	45	44.66				
85027	43	43	43.32	45				
85610	36	36.04	36.9	36				
87086	64	64	64	64				
87880	45	45	45	45				
88142	92	92.25	92.25	92.25				
88175	102.25	102.25	107	107				
88305	225	225	232	236				
89240	98	104.5	103.9	105				
90471	35	33	34	35				
90472	26	25	25	25				
90658	30	30	30	30				
90772	44	43	43	43				
90806	150	150	150	150				
92012	118	115	115	116				
92014	155	155	155	155				
92015	55	55	56	57				
93000	85	85	85	85				
93010	51	51	51	52				
93307	578	578	576	575				
93320	335	335	332	331				

93325	320	317	317	317
95117	40	39	40	40
97001	157	156	159	155
97010	35	35	34	34
97012	40	40	40	40
97014	39	38	39	39
97032	45	46	46	45
97035	43	43	43	43
97110	62.5	64	63	64.05
97112	60	60	60	60
97140	61.99	62.5	62	62
97530	62	63	62	62.25
98940	55	54	53	54
98941	65	65	65	65
98942	75.8	76	76	75
98943	50	50	50	50
99000	25	25	25	25
99202	128	127	127	127
99203	190	190	189	189
99204	275	273	273.3843	274.2
99211	54.5	52	52	52
99212	81	80	80	80
99213	110	110	110	110
99214	173	171	173	173
99215	250	250	250	250
99231	103	101	103	102
99232	150	150	150	150
99233	220	219.55	220	220
99243	280	275	277	277
99244	381	380	384	385
99283	324	328	328	331
99284	483	483	487	492
99285	691	707	707	716
99391	147	145	147	147
99392	160	160	160	160
99395	200	200	200	200
99396	220	216	219	219
D0120	48	48	48	48
D0140	75	75	75	75
D0150	80	80	80	81
D0210	130	131	132	133
D0220	28	28	28	28
D0230	24	24	25	25
D0272	42	42	42	42
D0274	60	61	61	61
D0330	105	105	106	106
D1110	90	90	90	90
D1120	66	66	67.17	67
D1203	35	35	36	36
D1204	35	35	35	35

D1351	52	53	53	53
D2140	144	145	145	147
D2150	175	178	176	179
D2391	168	168	169	170
D2392	215	215	217	219
D4341	250	250	250	250
D4910	140	140	140	140
D7140	150	150	152	153
G0283	40	40	40	40
Average	134.7122	134.1379	134.4303	134.3885